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Knowledge spillovers from clean innovation. A tradeoff between growth and climate?

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Abstract
Innovation policy faces a tradeoff between growth and climate objectives when the knowledge spillover externality from clean innovation is low compared to other sectors. To make such a comparison, we use patent data to estimate field-specific spillover returns generated by R&D support. Supporting Clean presents itself as a win-win opportunity, yielding global returns one-eighth higher than those of an untargeted policy. Nevertheless, only a modest portion of the returns stays within country borders, raising the question of whether national interests distort efficient allocation. Our policy simulations underscore the benefits of supranational coordination in clean innovation policy, potentially boosting returns by approximately 25% for the EU and over 60% globally. Moreover, the EU benefits strongly from US Clean innovation spillovers, impacting the debate on the Inflation Reduction Act. Overall, we identify no explicit innovation policy tradeoff in tackling the twin challenges of economic growth and climate change but emphasize the necessity for international cooperation.

Key words: innovation, knowledge spillovers, clean technology, innovation policy, green transition, net-zero, patent data
JEL Classification: O31; O33; O34; O38; Q55; Q58

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I. Introduction

Developed economies grapple with a dual challenge: reversing the trend of stagnating growth due to a productivity slowdown and cutting carbon emissions to tackle climate change. In addressing both problems, innovation will be vital as it drives productivity and fosters the development of decarbonization technologies (Stern and Valero, 2021). Nevertheless, private incentives to innovate fall short due to a double externality problem (Jaffe et al., 2005). Both clean and other innovations produce a knowledge spillover externality by providing valuable input for others' R&D efforts (Arrow, 1962). Clean innovations yield an additional, environmental externality because the the climate benefits they induce are not fully internalized. These externalities justify policy interventions to support innovation.

A first-best innovation policy allocates funds to R&D projects whose cost to the public is lower than the social value generated. However, such an ideal scenario is hard to attain due to public budget constraints, which are all the more stringent in the wake of the COVID-19 crisis. A next best strategy is a targeted innovation policy that favors sectors with high anticipated social returns. If the knowledge spillover externality of clean innovations happens to be subpar, supporting them comes with the opportunity cost of foregoing growth from other sectors (Popp and Newell, 2012). This opportunity cost needs to be traded off against the environmental externality, which is likely large but hard to pin down with precision, thus complicating the political debate (Tol, 2009; Stern, 2016).

To examine the significance of this tradeoff, we compare clean to other technology fields in terms of the knowledge spillover externality a targeted subsidy would create. Building on Guillard et al. (2023), we estimate the return rate of a hypothetical marginal subsidy within a specific technology field. The approach posits that directing subsidies to a field reduces the private cost of R&D, thereby stimulating additional innovations that would not have emerged based solely on their expected private returns. A positive social rate of return occurs when a subsidy's cost is lower than the value of knowledge spillovers from the innovations it creates. Return rates depend on three factors: (1) the cost to induce an additional innovation, (2) the number of innovations below the cost threshold defined by the minimum private value needed to pursue an idea, and (3) the spillover value created by such infra-marginal innovations. We estimate these determinants from patent data and we allow them to vary across technology fields and time. Applying this method to innovations patented between 2009 to 2018 delivers field-specific subsidy return rates for 42 countries, including OECD, EU, and China.

Our initial analysis juxtaposes global return rates for clean technology subsidies against those in other fields. The global rate of return encompasses the value of knowledge spillovers generated worldwide from a one-dollar subsidy in a given field. With a return rate of 135%, Clean ranks second among six broad fields, falling behind only to Electrical Engineering. The weighted average return rate across countries is 120%, indicating that a subsidy scheme focused on Clean generates roughly one-eighth higher returns than a uniform scheme that allocates subsidies proportionally to field sizes. Within the Clean category, fields such as Smart Systems and Offshore Wind outperform others, exhibiting return rates exceeding those in Artificial Intelligence and Biotechnology. The Clean subsidy return rates surpass the weighted average in most countries analyzed. For China, the EU, Japan, and the US, the clean advantage ranges between 13% and 18% above the weighted average, while in Korea, it is comparatively smaller at 4%.

The return rates accrued worldwide inform policies by a global planner, yet funding decisions are often influenced by national interests. Our spillover value measure employs the citation network between patent families, attributing a portion of the private value created by an invention to the spillovers from directly or indirectly cited inventions. This enables an analysis of spillover value flows by origin and destination countries. In subsequent analysis, we exploit this property to compute the returns to subsidy captured within a given region's borders, denoting them as the *local* returns. On average, approximately 23 percent of the clean spillover value is retained within the country of origin, with significant heterogeneity across countries. Based on national returns, the clean subsidy advantage is lower than that based on global returns, with a return rate close to the average national return rate across all fields. Consequently, targeting subsidies according to national return rates offers less incentive for supporting Clean. There are regional differences, however. In Europe, the clean subsidy advantage is *larger* when considering local returns; for East Asian countries, it remains roughly the same, while in the US, it vanishes entirely.

The fact that a large portion of spillovers cross country borders raises an additional question: are there important benefits from supranational coordination when designing clean innovation policy? In the next part of the paper, we take the stance of policymakers designing a clean innovation policy. We simulate optimal targeting of clean technology *sub-fields* – defined using a new classification scheme – to calculate the potential benefits of supranational coordination. Coordinating across countries can create value when national interests diverge from supranational ones. Consider a scenario where subsidizing Wind Power in Germany generates 30 cents to the dollar within the German economy and 40 cents globally, while another field, Smart Grid Systems, creates just 20 cents within Germany but 80 cents globally. The global planner would prefer Germany to support the latter, while a local planner would favor the former. The significance of such incentive misalignment depends on the differences in *ranking* of clean technology sub-fields based on national versus supranational returns. To estimate the benefits of coordination, we rely on our return rate measures to estimate the increase in supranational returns when moving from policies targeted based on national, to those targeted based on supranational interests.

Our results suggest supranational coordination yields substantial benefits, which grow with the number of countries participating. An EU-coordinated optimal policy results in returns to the EU that are one-fourth higher than those from a combination of nationally optimal policies. For the OECD, benefits are about 40% higher, and intriguingly, coordination by just the countries in the G7 can produce similar benefits. Globally coordinated policies are the most effective, yielding an increase in returns of over 60%. This additional benefit is primarily driven by Chinese clean innovation, which receives over 80% of all subsidies under such globally coordinated policy.

In the final section, we seek to contribute to the ongoing discussion on the Inflation Reduction Act (IRA). There are concerns, especially in Europe, that this $400 billion stimulus package targeting the adoption of clean technology may unfairly advantage US companies over their foreign counterparts due to its protectionist elements. However, any such distortions may be mitigated, at least in part, by the beneficial effects of knowledge spillovers from the US to international clean technology firms. Being a climate-focused demand-pull policy of unprecedented scale, the IRA is likely to foster advancements in US clean technology.[1] Such developments could then generate valuable knowledge spillovers overseas. Policymakers should consider these potential benefits before deciding on a potentially hawkish response.

Our method enables us to determine how supporting clean innovation in one country realizes spillover gains abroad. We compare such cross-border returns for several major innovation regions. Our findings indicate that, between 2009 and 2018, a 1 million US clean subsidy would have resulted in 1.26 million worth of spillovers in Europe, indicating that Europe benefits strongly from clean innovation support in the US. Comparing these figures to the returns from an untargeted subsidy scheme, we see ‘return flows’ of $1.18 to the EU per dollar of US subsidy spent.[2] In other words, Europe’s spillover benefit grows by approximately $0.08 per dollar spent when the US specifically supports the clean sector over a general policy. In summary, a

[1] There is convincing evidence supporting the hypothesis of induced (environmental) innovation (Popp, 2002; Newell et al., 1999; Peters et al., 2012; Dechezleprêtre and Glachant, 2014; Aghion et al., 2016; Barbieri et al., 2023). For a comprehensive review, see Popp (2019).

[2] A clean subsidy in Europe would yield only a 1.13 million worth of spillover benefits in the US. An untargeted subsidy of 1 dollar in Europe would create $1.15 of spillover benefits in the US. This implies that Europe derives more spillover benefit from innovation support in the US, and this imbalance is starker for clean subsidy.

dedicated push for Clean in the US benefits Europe through knowledge spillovers, compared to both the scenarios of no subsidy and non-clean subsidies. Whether such knowledge spillover effects outweigh the potential costs of lost business remains an open question, but they should arguably be considered an important factor in the debate.

The paper is organized as follows: The remainder of this section presents a comparison of our work with three areas of related research. In Section II, we outline the theoretical framework for estimating field-specific subsidy return rates, along with the data and metrics employed. Section III contrasts the return rates of clean R&D support with those in five other sectors. Section IV introduces the policy simulations used to determine the benefit of supranational coordination in creating clean innovation policy. Section V shifts the focus to an examination of cross-country knowledge spillover flows and their implications for the debate on the IRA. Section VI concludes.

A. Related literature

This paper adds to the body of research that empirically investigates spillovers from clean innovation. It closely aligns with a collection of papers that compare clean technology to a broad spectrum of other technologies. Popp and Newell (2012) highlight the possible opportunity costs of climate policies that stimulate innovation when they potentially crowd out innovation in other sectors. They find evidence of crowding out within individual companies but not across the wider sectors in the economy. The resulting opportunity cost is mitigated by the fact that clean innovations lead to more spillovers – they have a 6.5% higher chance of being cited than other patents from the same group of firms in their study, which covered the period 1971-2002. Barbieri et al. (2020) examine the entire patent landscape from 1980 to 2012 and discover that clean patents receive 0.27 more citations (the average in their sample is 0.9 citations). They also find that clean technology is more novel and draws from a wider body of preceding work.[3] In contrast, Bjørner and Mackenhauer (2013), who analyze knowledge spillovers within a narrower sample of Danish firms from 2000 to 2007, found no evidence of greater spillovers by clean technology. Their work adapts the conventional production function method for estimating spillovers (see Hall et al. (2010)) to compare the effects of clean and non-clean knowledge stocks on firm value-added. As opposed to these studies, we estimate the returns from a marginal subsidy in different sectors rather than analyzing differences in *average* spillovers. To measure spillovers, we merge the

[3]Other research confirms that clean innovations combine knowledge from a wider scope of the knowledge space, as demonstrated by the patent classes they cite, are assigned to, and by their more frequent use of (broad) collaboration (De Marchi, 2012; Orsatti et al., 2020; Fusillo, 2023).

citation network with measures of the private value of innovation. This enables us to account for *indirect* spillovers – i.e. spillovers from inventions that are more than one degree away in the citation network – and accommodate for the variation in the value of citing inventions when assessing knowledge spillovers.

A second set of papers looks for evidence of knowledge spillovers within clean technology alone or compares these to spillovers generated by 'dirty' technologies. It is motivated by a substantial body of theoretical work investigating under what circumstances environmental challenges can be addressed while maintaining economic growth (Nordhaus, 1994; Bovenberg and Smulders, 1995; Porter and Linde, 1995; Popp, 2004; Hart, 2004; Stern, 2009; Acemoglu et al., 2012). The presence and extent of knowledge spillovers from clean technology are crucial factors in these models, thereby influencing the need for governmental intervention, the comparative benefits of demand-pull versus technology-push interventions (or a combination of both), and the optimal duration of intervention. On the level of individual inventions, Dechezleprêtre et al. (2022) find that clean innovations generate about 60% higher knowledge spillovers than dirty innovations.[4] Additionally, they use market value assessments of patents in Tobin's Q regressions to demonstrate that the value of innovations built on clean technology is, on average, higher. At the firm level, Aghion et al. (2016) employ innovation production function estimates to reveal significant path-dependence in generating both clean and dirty innovations. Their results imply that companies find it more profitable to innovate in the sector (Clean or Dirty) where they and nearby firms possess more prior knowledge. More evidence of clean path dependence has been discovered at the country level in studies using patent data and trade patterns (Perruchas et al., 2020; Santoalha and Boschma, 2021; Moreno and Ocampo-Corrales, 2022; Mealy and Teytelboym, 2022). Generally, empirical evidence aligns with the notion that directed technical change can lead to a long-term equilibrium where private incentives for clean innovation dominate, provided there is a sufficiently large stock of clean knowledge (Acemoglu et al., 2012). Temporary interventions supporting clean innovation are required to guide technology development toward a clean equilibrium. While our findings support path dependence, our primary focus is on the potential opportunity cost of policies that use scarce public resources to implement clean innovation policy. Our results further reinforce the argument for an innovation policy that steers efforts towards clean technology development, as these initiatives do not appear to divert public funds away from vastly more profitable alternatives.

[4]Their measure of spillovers accounts for indirect spillovers, as gauged through the patent citation network, but it differs from ours in that it does not weigh citations by their private value.

A final group of related papers investigates the geographical aspect of clean knowledge spillovers. Their findings confirm the idea that spillovers are, to some degree, geographically localized (Jaffe et al., 1993; Thompson and Fox-Kean, 2005), but they also offer additional insights specific to clean technology. Verdolini and Galeotti (2011) examine 38 countries and discover that an increase in foreign knowledge stock leads to more innovation compared to a similar increase in domestic knowledge stock. This effect is particularly pronounced for countries with the least energy-related innovation activity. Conti et al. (2018), using methods from Caballero and Jaffe (1993), compare the localization of spillovers in 15 EU countries with those in the US. They find higher localization in Europe, but such fragmentation of knowledge declined significantly after 2000 – and this pattern is unique to clean technology, not other high-growth fields such as 3D, IT, Biotech, and Robotics. Ocampo-Corrales et al. (2021) examine citation patterns in European regions and find that clean technology relies more on knowledge flows from distant places compared to other technology categories (both traditional and cutting-edge). Our results generally affirm the importance of international knowledge spillover flows, with internalization rates never exceeding half and averaging 23%. We also observe that internalization rates for European countries are larger for clean technology than for other technologies (but the opposite holds for the US). Our analyses build upon these findings by explicitly focusing on the implications of knowledge flows across national borders for national and supranational innovation policy.

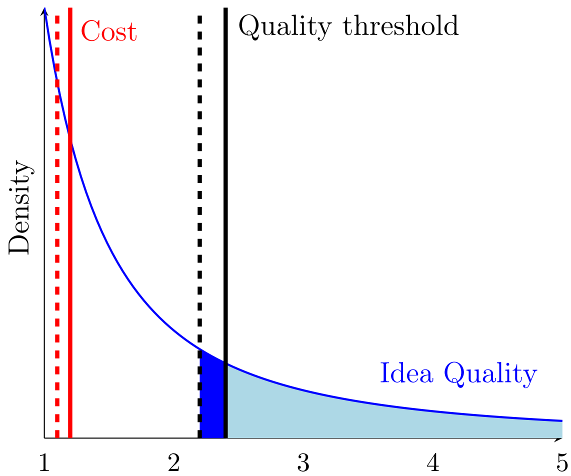
II. Estimating field-specific spillover returns to subsidy

A. Theoretical framework

Our objective is to estimate the impact of a subsidy on the total value generated by innovations in a given technological field a. We define the total value as the sum of private revenues created by an invention and the value of spillovers it produces for other inventions. At the center of our approach is the idea that a subsidy targeting a technological field may not stimulate the *average* innovation. Rather, we assume that the subsidy reduces the cost of innovation, enticing innovations not viable based on their expected private returns alone. Accounting for potential differences in spillover rates and costs for inframarginal innovations across fields, we employ a simple model of innovator behavior devised by Guillard et al. (2023) (henceforth, GMMTV).

The model portrays an innovator drawing ideas with varying quality from a Pareto distribution. Idea quality serves as an indicator of the potential private value an innovator can obtain once the idea is transformed into an innovation. The realized private value is uniformly distributed between 0 and the idea quality. To convert ideas into innovations, a fixed cost must be incurred, resulting in an idea quality threshold of twice the innovation cost above which ideas will be pursued. Figure 1 illustrates this situation, where the light-blue-shaded area represents ideas pursued in equilibrium. A subsidy lowers the innovation cost, and thus the idea quality threshold, inducing innovations in the dark-blue-shaded area.

Figure 1: Costs and the idea quality threshold



Notes: Visual representation of innovation production. Innovators draw ideas from a Pareto idea quality distribution (the blue line). The idea quality provides a signal about the value of the innovation that might result from the idea. To pursue an idea, the innovator incurs a cost (red vertical line). Only ideas for which the quality is high enough are pursued (solid black line). Prior to the subsidy, all ideas in the light-blue-shaded area are pursued. The subsidy pushes down the cost, and therefore the idea quality threshold (now the dotted black line), resulting in additional ideas being pursued into innovations (ideas in the the dark-blue-shaded area). The returns to the subsidy are determined by the total cost of the subsidy (which scales with the cost threshold of the field), the mass of ideas present below the quality threshold (which depends on the shape parameter of the Pareto distribution), and the expected spillover value those ideas generate (which is approximated by the spillovers created by observed innovations of relatively small private value).

In this setup, GMMTV calculate the return rate for a subsidy directed at field a. The return rate is derived as a function of the private and spillover value distribution in the field, along with the cost parameter c and idea quality distribution shape parameter α. To obtain this, they differentiate the total value of ideas pursued in a field with respect to a decrease in the innovation cost. We refer to their paper for details, but their derivation results in the following expression.

$$ReturnRate_a = \frac{1}{c_a}\frac{1}{\#A}\sum_{i \in A} SV_i \times (\alpha_a - \alpha_a \times \mathbb{I}\{PV_i > 2c_a\} + \mathbb{I}\{PV_i < 2c_a\}) \qquad (1)$$

where i indexes elements in the set A of all innovations pursued in field a. SV_i and PV_i represent the spillover value and private value generated by innovation i; c and α are time-field specific parameters corresponding to the innovation cost and the shape of the idea quality distribution. $\mathbb{I}\{PV_i > 2c_a\}$ evaluates to one if $PV_i > 2c_a$ and $\mathbb{I}\{PV_i < 2c_a\}$ evaluates to one if $PV_i < 2c_a$. This implies that only the spillover value of innovations below the idea quality cost thresholds are used to compute spillover returns (the term inside the summation sign evaluates to 0 when $PV_i > 2c_a$). This feature emphasizes the importance of spillover values *induced by the subsidy* rather than the average spillover value. As expected, returns decrease as the cost of innovating drops, reflecting the higher expense of inducing additional innovations in fields with increased costs. A higher α value yields more ideas just below the quality threshold, subsequently boosting the returns.

B. Data and measurement

The goal of our approach, guided by Equation 1, is to measure the return rate of a hypothetical additional subsidy in a given field, a. To do this, we need observations of the spillover and private value distributions, as well as estimates for the cost and shape parameters of the idea quality distribution. To obtain this information, GMMTV combine patent-level measures of private and spillover values with structural estimates of c and α.

Data. Our analysis uses global patent information from the PATSTAT Global Autumn 2021 database. PATSTAT identifies innovations through patent families, which is necessary since organizations must file patent applications in each jurisdiction where they seek protection. Consequently, one invention often corresponds to multiple patent applications. A patent family encompasses all patent applications associated with a single innovation. The database provides various relevant details extracted from patent documents published during the examination process, including technological classes, patent citations, patent claims (specifying the exact scope of protection sought by the patent), filing time, the number of patent applications linked to the invention, the applicant name (the individual or organization that will hold the patent right), and the inventors' address on the patent. We use the Orbis database to acquire a harmonized identifier for applicants across distinct patent families. This allows us to purge self-citations between patents of the same firm, which is desirable as those citations represent cumulative innovation within a firm and therefore are not part of the knowledge externality we aim to measure.

To identify clean technologies, we use the *Y02* tag in the CPC classification that is assigned to 'Climate Change Mitigation Technologies' by the receiving patent office. We further identify more detailed clean sub-fields using a classification scheme devised by the UK Bureau for Energy and Industrial Strategy (BEIS). After identifying 11 key clean innovation sectors, it uses the Espacenet CPC search tool to assign patent classes to each sector. The methodology relies on expert input and the academic literature to validate the classification scheme. Appendix B provides a detailed overview of this classification exercise. To assign innovations to countries, we use inventor address information – bypassing the issue that multinational firms may assign the patent to a subsidiary of their choice, which may or may not reflect the actual location of the inventive activity. To collect country information, we combine data available in PATSTAT (which parses country codes from inventor addresses on the patent) with data from de Rassenfosse et al. (2019), who complement address information from PATSTAT with that from national patent offices and geo-code addresses.[5]

Private value. We employ a two-step procedure to calculate a private value PV_i for each invention. In the first step, we use data from an event study approach developed by Kogan et al. (2017), which allows deducing the value of individual innovations from the change in the innovating firm's share price – relative to the market – around the time when a patent for the underlying invention was granted. In the second step, we use these value estimates to predict invention monetary values based on several patent indicators that correlate with private value and are observable for all innovations. This approach addresses the issue that only a small fraction of all innovations belong to stock-listed firms. The predictors employed include the timing of the application, technological classification, the number of patent filings in the family, and the number of claims. For example, suppose a patent belongs to class A61K31 ('Medicinal preparations containing organic active ingredients'), was filed in 2009, and has 5 claims and 7 filings in its family. The private value of this invention is the average of the stock-market-based values of all inventions with exactly these characteristics. GMMTV demonstrate that the private values based on this predictive model correlate well with the stock-market-based estimates in the sample where both measures are available. The correlation between the two measures of private value is 0.51 for the actual values and 0.60 when taking the logarithm and standardizing the values.

Spillover value. Relying on patent citations found on the front page, we can trace the connections between various innovations, establishing a 'paper trail' of knowledge linkages. This information allows us to determine which innovations benefit from the knowledge of the cited innovation, thereby enabling us to construct a network of knowledge spillovers. GMMTV develop Patent Rank (P-Rank) to measure the economic value of knowledge spillovers as captured by patent citations. Drawing inspiration from PageRank – Google's original algorithm for ranking

[5]These two data sources are complementary. Using PATSTAT only, 19,112,005 innovations of the total of 52,997,635 innovations applied for between 1980 and 2018 can be assigned to at least one country. Using just the geo-coded information results in 9,943,422 innovations assigned, such that a total of 29,055,427 (or 54.8%) innovations is assigned.

web pages – Patent Rank employs citations between patent documents instead of hyperlinks between web pages to assign an index of importance to every invention throughout the entire citation network. Specifically, we assume that any innovation i has a value of V_i comprised of the sum of its private value PV_i and external (i.e., spillover) value SV_i.

$$P\text{-}rank = V_i = PV_i + SV_i = PV_i + \sigma \sum_{j \in F_i} \frac{1}{N_j} V_j \tag{2}$$

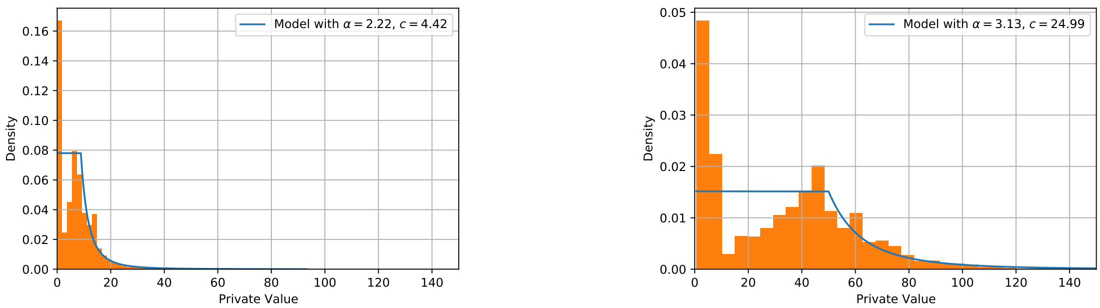
The underlying intuition of this measure is that a portion of an innovation's total value originates from its capacity to access the available body of knowledge. The size of this portion is encapsulated by the value of σ and is allocated as a spillover value to the innovations it references. As such, σ represents the marginal contribution of spillovers to an invention's value. Instead of explicitly estimating σ, we rely on a proxy from the literature. In a sample of clean car technologies, Aghion et al. (2016) find that the elasticities of own and external knowledge stock contributions to the generation of new innovations are roughly similar. Consequently, we set σ to 0.5, corresponding to an equal contribution from a firm's own R&D efforts and the stock of available knowledge. GMMTV show that changing the value of σ significantly affects the magnitude of returns (i.e., a higher value implies higher returns as indirect linkages are valued more highly), but the ranking of different innovations or fields in terms of their spillovers remains stable.

The set of innovations citing innovation i is denoted by F_i, and each innovation in this set is indexed by j. The number of innovations cited by j is represented by N_j, which means that the spillover portion of innovation j (σV_j) is equally distributed among the inventions it cites. Since V_j depends on both the private value of innovation j and its spillover value to innovations that cite j, Equation 2 corresponds to a system of equations for each innovation in the citation network. To solve this system, GMMTV employ an iterative algorithm that converges to the solution, bypassing the computational burden associated with inverting a large matrix.

Cost and shape parameter. The cost and idea quality distribution are not directly observed in the data. GMMTV use the model's structural assumptions of innovator behavior to estimate these parameters from the observed private value distribution. It is crucial to recognize that the private value represents the market's expected returns from an innovation, considering its R&D cost as sunk (as the R&D has been completed by the time of grant). Consequently, the observed private values should be greater in a field with higher R&D project costs because only projects with *expected* returns sufficient to cover these higher costs are pursued. However, note that it is still possible to observe innovations with low value as even ideas that initially seemed good could turn out to be of low value after further research. Furthermore, the skew of the idea quality distribution influences the shape of the observed private value distribution (a highly skewed quality results in highly skewed private returns). In essence, the model parameters can be employed to derive an ex-post distribution of private value. We can then deduce the two parameters by fitting the modeled private value distribution to the one observed in the data. Specifically, GMMTV use the model to derive various quantile values of the distribution as a function of the two parameters of interest. An evolutionary algorithm is employed to find the α and c that minimize the difference between actual and modeled distribution quantile values. This algorithm is run for each year in the data and for 41 broad technology fields. Figure 2 demonstrates this approach for two common fields, Semiconductors and Organic Fine Chemistry, for the year 2010.

Figure 2: Actual vs modeled private value distributions

(a) Semiconductors (b) Organic fine chemistry



Notes: Comparison of actual and modeled private value distributions for the two fields with the lowest (a) and highest (b) estimated cost. The histogram plots the actual private value distribution in the field, and the blue line shows the modeled density. Cost (c) and alpha (α) are estimated for each field (41) and year (10) combination. Plotted examples are based on the year 2010.

The estimated parameter values of α and c for each area generate the blue lines in the graphs. The histograms display the private values estimated from the data. The modeled distribution is flat until twice the estimated cost, and the modeled private value does not fit well up to this 'kink' in the modeled distribution. However, the distribution of private values in these low-value regions is not relevant for estimating returns on marginal subsidies (see Equation 1). More important is that the observed kink in the actual distribution corresponds to the kink in the modeled distribution, as it is based on this kink costs are estimated. The kink in the modeled distribution for Semiconductors occurs at a private value of around \$9 million, suggesting that only ideas with an expected value of at least \$9 million will be developed in this field. The density of the modeled and observed private value distribution decreases quite rapidly for private values above this threshold, corresponding to a relatively small estimate of α at 2.22. In contrast, panel (b) of Figure 2 shows the estimated model for *Organic fine chemistry*, which is found to have a much higher idea development cost, of around \$25 million, and much flatter modeled and observed distributions above this value, corresponding to a larger value of α at 3.13.

C. Descriptive statistics

Table 1 presents the summary statistics of the principal input variables used in the computation of subsidy return rates. Our sample covers more than 7 million patent families. These patent families represent those for which a minimum of one inventor can be attributed to a country in the OECD, the EU, or China. As seen in the commonly recognized pattern of a sizeable skew in patent value distribution, the mean exceeds the median by approximately 36%, and the highest value is more than 200 times larger than the median (values are reported in million 2015 US dollars). The pattern for SV (the spillover value) is even more remarkable, with the mean almost tenfold the median. It should be noted that the minimum private value is invariably strictly positive (with \$250 being the minimum in our sample), while the minimum spillover value is zero in instances where the patent does not receive any forward citations.

The table further details the means of PV and SV across both fields and combinations of fields and years. We see considerable variation in both value types, even when considered at the aggregated field level. The mean private value of an innovation oscillates from \$9.9 million (Clean Cars) to \$40.4 million (Organic Fine Chemistry), while the average spillover value spans from \$2.4 million (Mechanical Elements) to \$10.2 million (Organic Fine Chemistry). At the level of field-year combinations, this variance is larger (compared to the field level, the standard deviation at this more detailed level rises by 36% for PV and 118% for SV), suggesting that our measures capture significant heterogeneity across different fields and temporal spans.

Our methodology for calculating return rates – which focuses on comparing fields based on spillover value – is at least partially driven by the field-level variations in private value. The innovator considers both the anticipated private returns of an R&D project and the cost of innovation, which means that variation in private value reflects the cost of innovating within a specific technology. From a policy perspective, these costs determine the resources needed to induce an innovation (and resulting spillover value), hence playing a crucial role in the formulation of effective subsidy schemes. As previously outlined, these considerations are encapsulated by parameters α and c, which are estimated at the field-year level.

The bottom section of Table 1 probes into the variability of these input parameters at the field-year level, while the center section averages them out to the field level. In line with expectations, we find considerable fluctuations in these parameter estimates across both fields and time. For the average field, the cost of innovation is pegged at approximately \$13.6 million, fluctuating between \$8.9 million (in Semiconductors) and \$20.2 million (in Organic Fine Chemistry). The idea quality distribution shape parameter, α, dictates the quantity of ideas that will turn out to be privately viable should the cost of R&D fall. The highest level (in Thermal Processes) is over twice the lowest level (in Basic Materials Chemistry). To interpret the magnitude of this difference, consider two Pareto distributions with the same mean but with shape parameters of 2.1 and 4.5, the minimum and maximum values we observe. A cost reduction from \$13.6 to \$12.6 million induces 1.88 times more innovations in the high compared to the low α case. At the field-year level, the standard deviation for α and c is approximately one-third of the average. Both parameters show a moderate correlation of 0.40, whereas c shows a stronger correlation to the average PV (0.65), and α exhibits a slightly negative correlation to PV (-0.15). Intriguingly, SV demonstrates a negative correlation to PV at this level (-0.18), and by extension to both α (-0.24) and c (-0.46). Combined, these patterns suggest considerable variation in the key input variables for the subsidy return rates across fields (and time).

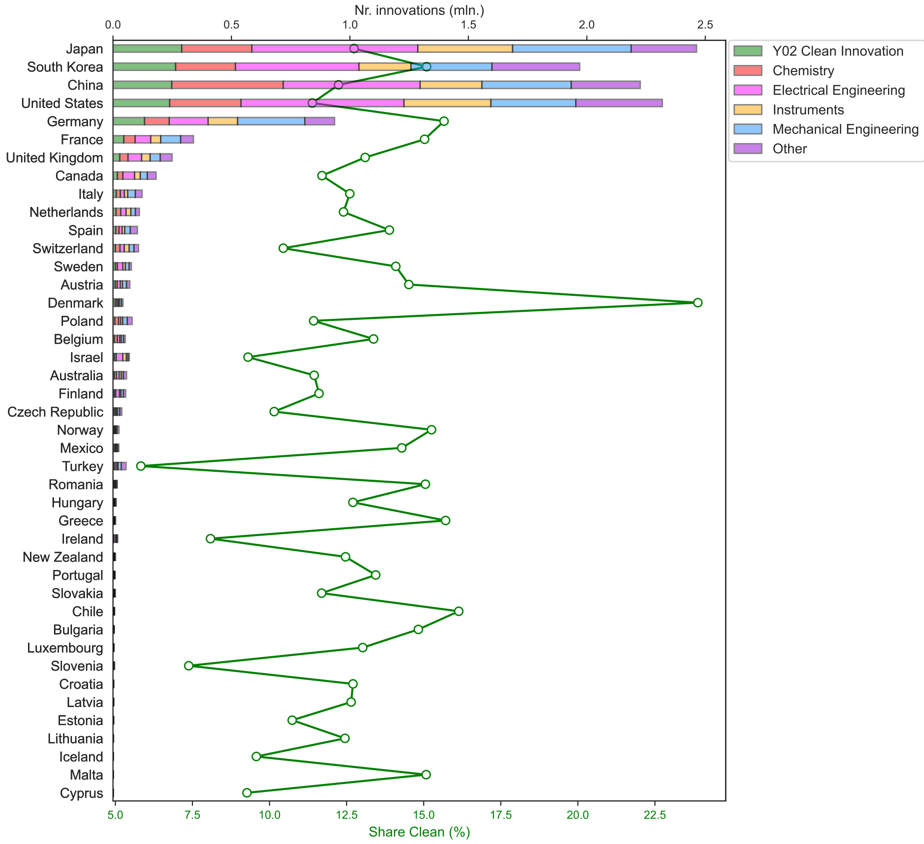
Table 1: Summary statistics

	Obs.	Mean	S.D.	Min.	25th pct.	50th pct.	75th pct.	Max.
Innovations								
PV	7,017,805	17.44	20.24	0.0	2.62	12.83	23.57	590.05
SV	7,017,805	5.09	13.94	0.0	0.0	0.64	4.9	3236.8
Fields								
PV	39	19.6	6.76	9.86	14.7	18.59	22.2	40.41
SV	39	5.62	2.11	2.39	3.74	5.48	7.26	10.24
α	39	2.9	0.53	2.11	2.52	2.79	3.23	4.52
c	39	13.61	2.36	8.85	11.84	13.32	14.71	20.17
Field-years								
PV	390	20.34	8.84	6.15	14.16	18.6	24.21	56.55
SV	390	5.34	4.6	0.04	1.61	4.32	8.08	25.6
α	390	2.93	0.96	1.48	2.4	2.71	3.17	8.5
c	390	14.05	4.52	5.54	10.7	13.14	17.0	29.33

Notes: Descriptive statistics of key parameters that determine subsidy return rates. The upper panel is at the level of the innovation, the middle panel at the level of the technology fields used for the estimation of c and α, the lower panel at the level of field-year combinations. PV, SV, and c are expressed in millions of 2015 US dollars.

Figure 3 parses out the count of innovations by the countries in our data set and general technological fields.[6] Each country, selected from the OECD, the EU, and China, has stacked bars corresponding to the top x-axis, denoting the count of innovations by field. The green line corresponds to the bottom x-axis and shows the share of Clean in all innovations. One notable observation is that the majority of innovation, both in general and in Clean, is concentrated in a small number of countries. Japan, the US, China, Korea, and Germany combined account for approximately 83.3% of all innovations and about 83.8% of all Clean innovations. Among these innovation powerhouses, Germany and Korea surpass the 15% mark for the share of clean innovations, while the US and China hold shares of 11.4% and 12.2%, respectively. The proportion of innovations in Clean varies considerably among countries, with Turkey (5.8%), Slovenia (7.4%), and Ireland (8.1%) trailing, and Denmark (23.9%), Chile (16.1%), and Greece (15.7%) leading the way. On average, a country holds a 12.7% share.

Figure 3: Innovations by country



Notes: Innovation counts by country across six technology sectors (ordered by the number of Clean innovations). Stacked bars, matching the upper x-axis, display counts in millions, using 'full counting' for multi-sector or multi-country innovations. Green circles, aligning with the lower x-axis, represent each country's share of clean innovations.

[6] Note that an innovation might be categorized into several fields (if it is assigned multiple technology classes spanning different high-level technology domains) and multiple countries (in case of cross-country inventor teams). Since we are not making assertions about the total volumes of innovation, we find no compelling reason to complicate the analysis and its interpretation with fractional counting.

III. The relative returns to clean R&D support

Our analysis focuses on comparing projected returns from an R&D subsidy for clean technology with those in other fields. We use variations of equation 1 tailored to specific technology sectors or countries. Section III A examines *global* spillover return rates, incorporating all innovations citing the focal one, regardless of origin. This scenario assumes a policymaker has no preferences with respect to where spillovers are realized. Conversely, Section III B investigates *local* returns by employing an adapted version of SV_i that considers only citing innovations from the same country as i.[7]

A. Global returns

Figure 4a compares the average return rate of Clean to five broad sectors of innovative activity. The width of each bar depicts the size of the field in terms of the number of innovations. The dotted vertical line shows the weighted average return rate across all innovations in our sample, which consists of 42 countries.[8] This average return rate represents an innovation policy that allocates subsidies proportionally based on the level of innovation activity in each sector, akin to a tax credit on R&D costs. Under this 'flat policy', the return rate stands at 120%, indicating that spillovers yield more than twice the public investments in knowledge creation. Focusing on clean technology, a targeted policy yields a significantly higher return rate of around 136%, which represents an additional gain of roughly one-eighth compared to the flat policy. Among the sectors, Electrical Engineering, including, among others, Telecommunications, Computer technology, and Audio-visual technology, would generate even higher returns, reaching approximately 168%. Conversely, targeting Mechanical Engineering fields, such as Textile and Paper Machines, Handling, and Mechanical Elements, would yield lower effectiveness, with return rates hovering around 80%.

Figure 4b compares Clean technology to several other fields that have been proposed to benefit from targeted industrial policy, including Artificial Intelligence, Biotechnology, Aerospace, Robotics, and 3D printing. Notably, sub-fields within the Clean domain, such as Smart Systems and Building Fabric[9], exhibit impressive return rates of 168% and 145%, surpassing prominent fields like AI (136%), Aerospace (93%), and Biotech (81%). Moreover, considerable variation

[7] Both direct and indirect knowledge flows are accounted for in local and global spillovers. For instance, indirect knowledge transfers occur when a US innovation is cited by a Japanese one, which is then cited by another US innovation. Each of these is factored in when calculating the local spillover value for US innovations.

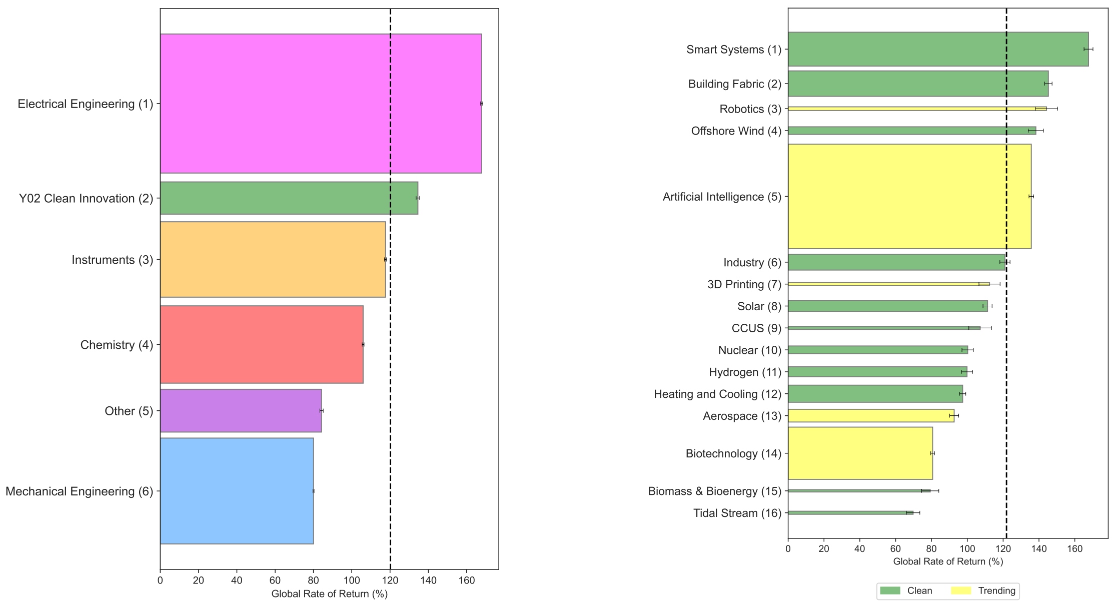
[8] The five broad sectors are based on the most aggregate classification level described in Schmoch (2008).

[9] Please refer to Appendix B for a detailed description of the derivation of these sub-fields.

exists among these smaller Clean sub-fields, with the least-performing ones yielding no more than half the returns of the highest-performing ones. This observation is unsurprising, given that Clean contains a diverse set of technologies grouped under a common application domain rather than representing a technologically homogeneous entity.

Figure 4: Global returns – weighted average across countries

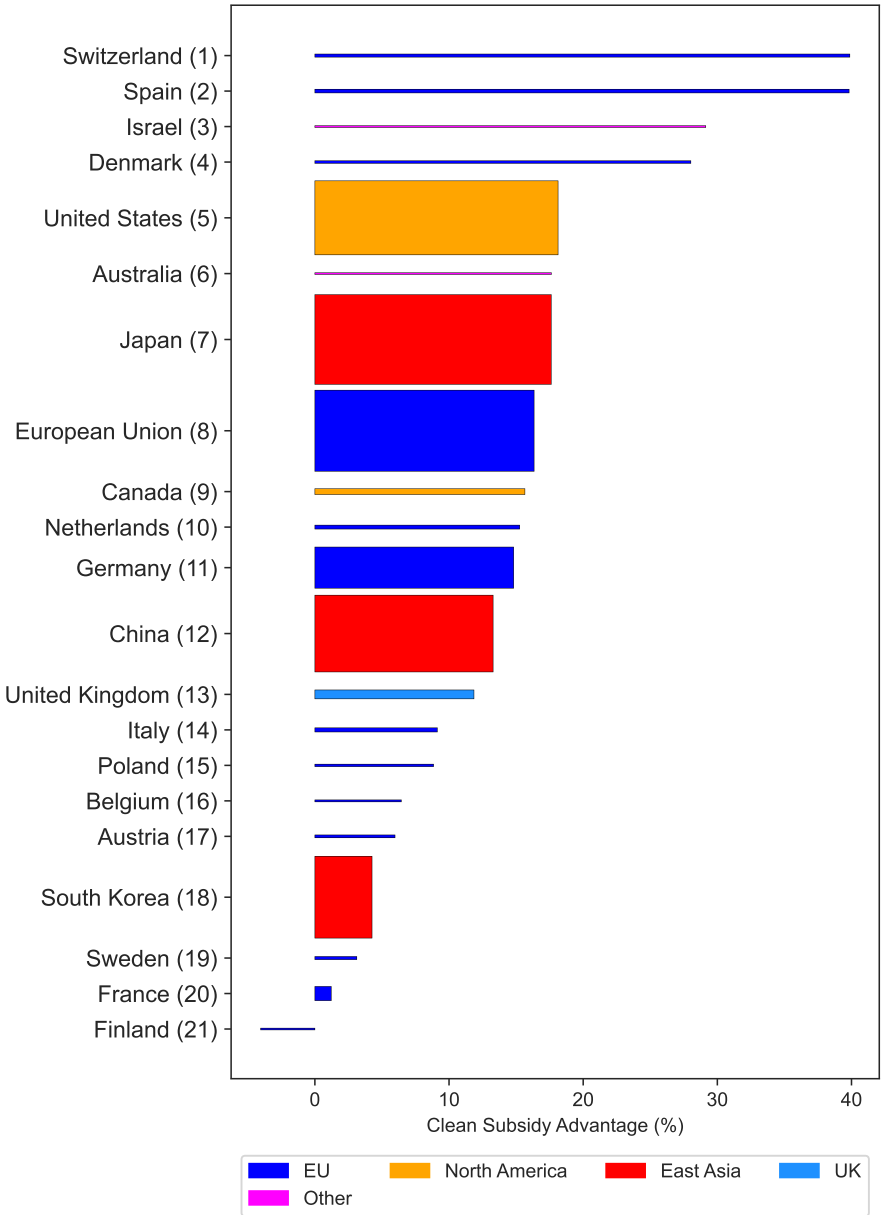
(a) All innovations **(b)** Benchmark Clean and Trending



Notes: Expected return rates to R&D subsidies by technology field (y-axis) along with 95% confidence bands. The (vertical) width of a bar indicates the field size, measured by its number of innovations. The x-axis displays the return rate (in %) to an additional $1 of R&D subsidy in the field, with returns based on the spillover value that subsidy-induced innovation creates globally between 2009 and 2018 (i.e., $ReturnRate_a$ in equation 1). The left-hand figure includes the entire sample of innovations, divided into Clean and 5 other broad sectors. The right-hand figure compares sub-fields within Clean (see Appendix B for a detailed description) to several trending technology fields. The dotted line represents the weighted average across technology fields for the sample under consideration.

Proceeding with a detailed examination of individual nations' data allows us to verify if the established pattern, as discerned on a weighted average basis, persists at the individual country level. Figure 5 presents our calculated 'Clean Subsidy Advantage' (CSA), an indicator derived by dividing the returns associated with Clean by the weighted mean return rate and subsequently deducting one. The figure incorporates only the 21 nations that account for a minimum of 2000 patented inventions during our period of study spanning from 2009 through 2018. The returns generated by Clean exceed the average in a majority of these nations but with considerable heterogeneity. When examining the primary innovators in clean technology – Japan, China, the EU, the US, and Germany – the relative returns appear fairly consistent, with clean initiatives generating returns between 13% and 18% superior to the weighted average returns (i.e., the flat policy). Korea emerges as an outlier among these leading innovators, with a relatively modest CSA, pegged approximately at 4%. Conversely, in Finland, clean initiatives yield returns that are below average, whereas, in Switzerland and Spain, the relative returns nearly reach 40%.

Figure 5: Clean Subsidy Advantage by country – Global returns



Notes: Clean Subsidy Advantage by country (y-axis). The (vertical) width of a bar scales with the number of clean innovations in the country. All countries in our sample with at least 2000 clean innovations are included. The Clean Subsidy Advantage for a country (on the x-axis) is calculated by dividing the global return rate from an extra subsidy in Clean by the weighted average global return rate across all country innovations. We then subtract one and multiply by 100% (it corresponds, for each country, to the height of the green bar, divided by the dotted line in Figure 4).

B. Local returns

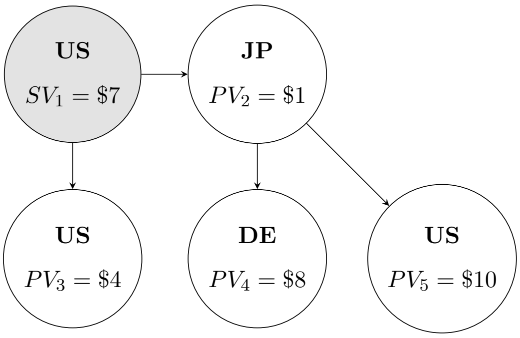
The return rates displayed so far rely on a version of equation 1 that incorporates the global generation of spillover value. In other words, SV_i arises from the private value of innovations cited, reaped by innovators irrespective of their geographic location. However, innovation policy is predominantly orchestrated by national governments whose primary interest lies in the value yielded within their respective national boundaries. To discern whether the substantial return rates associated with Clean are maintained when viewed through this lens of national interest, we probe an alternate formulation of the return rate. Herein, SV_i is computed as the spillover value resulting from innovations emanating from within national borders.

The P-Rank algorithm offers a relatively simple way to accomplish this. Consider a spillover flow network of a US invention as drawn in Figure 6. This invention serves as a foundation for another US invention and one from Japan. Subsequently, the Japanese invention becomes a basis for a German and another US invention. Figure 6a illustrates the calculation of the global SV_1. Solving the system of equations as per expression 2 for this simplistic network yields an SV_1 value of 7.

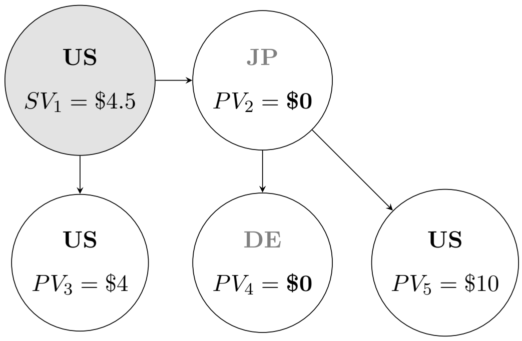
In order to compute the local SV_i – defined as the spillover value induced through innovations generating private value within the US – we may effectively assign zero to the private values of inventions outside the US and then recalculate P-Rank. The modified network is represented in Figure 6b. The reason to set PV_j of non-US inventions to zero, rather than eliminating them from the network entirely, is to retain the indirect spillover links to innovations within the US; i.e. we allow for the possibility that one US inventor can benefit from another US inventor via an inventor outside the US (in Japan, say). The local spillover value SV_1 stands at \$4.5 and depends on both PV_3 (through a direct spillover link) and PV_5 (via an indirect spillover link).

Figure 6: Calculating local spillovers

(a) Global SV



(b) Local SV



Notes: Illustration of the calculation of knowledge spillovers. Circles represent patented innovations, with country codes indicating the patent's inventors. Lines represent citations between patent families. The global spillover value of a particular innovation (upper figure) is calculated by summing its private value and the value of the spillovers it creates (see also equation 2). Let us calculate $SV_1 = PV_1 + SV_1$. We need to consider the innovations that cite 1, which are innovations 2 (from Japan) and 3 (from the US). As per equation 2, $SV_1 = \sigma(V_2 + V_3)$, because $N_2 = N_3 = 1$ (each citing innovation only cites innovation 1). As innovation 3 is not cited, we have $V_3 = PV_3 = \$4$. Innovation 2 is cited by innovations 4 and 5, so $V_2 = \sigma(V_4 + V_5)$, recognizing again that $N_4 = N_5 = 1$. As both innovations 4 and 5 are not cited, we have that $V_4 = PV_4 = \$8$ and $V_5 = PV_5 = \$10$. Now we see that $SV_1 = \sigma(PV_3 + PV_2) + \sigma^2(PV_4 + PV_5) = 0.5(\$4 + \$1) + 0.5^2(8 + 10) = \$7$. To calculate local SV_1, we simply set all private values of innovations from foreign countries (non-US in this case) to zero, and repeat this calculation to see that $SV_1 = \sigma(PV_3 + PV_2) + \sigma^2(PV_4 + PV_5) = 0.5(\$4 + \$0) + 0.5^2(\$0 + \$10) = \$4.5$.

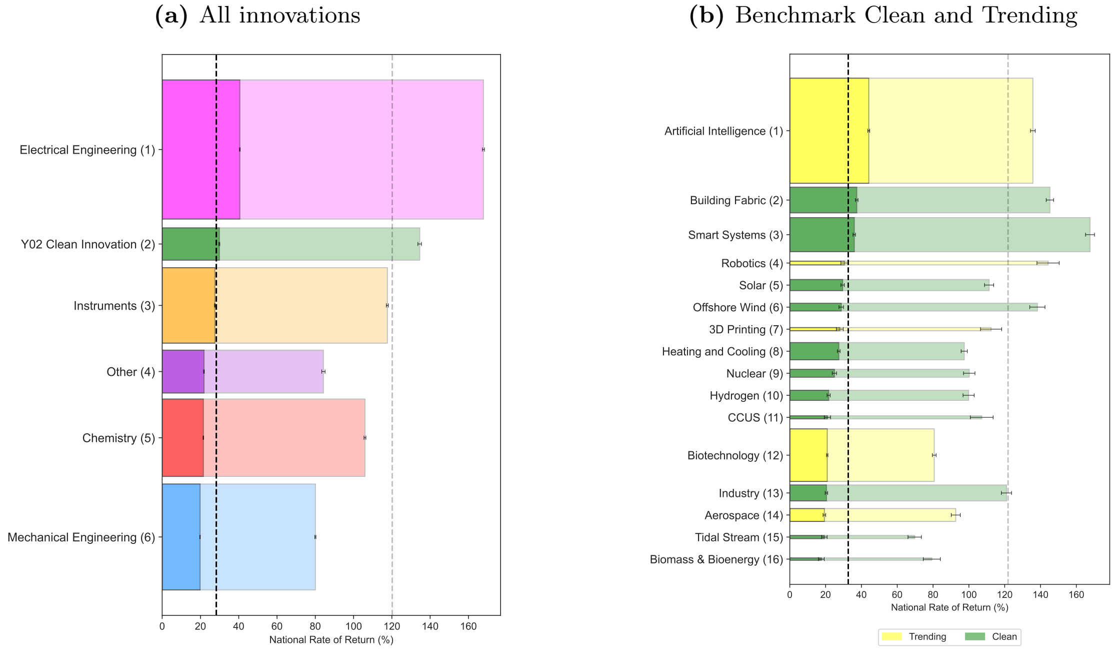
Figure 12 in Appendix A illustrates the degree to which the spillovers of clean knowledge remain confined within national borders. Solid bars represent the average local SV, while translucent bars denote the average global SV. The width of each bar corresponds to the volume of clean innovations. An initial observation is that the spillover value retained within national boundaries is relatively limited. Based on a weighted average calculation, merely 23.3% of an invention's total spillover value is retained within the country of origin. The localization of clean knowledge spillovers marginally trails behind the overall spillover localization, which stands at 24.2%.[10] Moreover, it is evident that smaller nations retain a significantly smaller proportion of their spillovers. The fraction of spillover value contained within the borders of Germany,

[10]For brevity, we have not included the corresponding figure for the entire set of innovations in our sample, which bears a close resemblance.

France, and the UK amounts to 21.2%, 11.4%, and 4.8%, respectively. Conversely, Korea and the US demonstrate relatively high proportions of contained spillovers, with 46.6% and 31.7%, respectively. The EU as an aggregate retains 29.0%, while China's figure, 13.9%, is somewhat smaller than might be anticipated based on its size. Intriguingly, the rate of localization for Clean innovations, as opposed to all innovations, is higher in the EU (29.0% versus 23.1%), but notably lower for the US (31.7% versus 41.0%). This trend indicates that national interests in supporting Clean innovation may be relatively large in the EU – a pattern we delve further into below.

Figure 7 reiterates our examination of subsidy returns at the technology level using local SV, that is, the return rate derived from Equation 1 but using spillovers realized within the innovating country. Solid bars depict local return rates, while translucent bars re-present the global return rates previously discussed. Upon examining broad innovation sectors in Figure 7a, it can be observed that the ranking of broad fields remains consistent with the exception of Chemistry, which descends from fourth to fifth place. This implies that local returns contribute a relatively smaller proportion of its global returns. Local returns to Clean subsidy amount to 29.9 cents per dollar invested, only slightly surpassing the weighted average of 28.3 cents per dollar. When juxtaposed with global return rates, this demonstrates that while Clean still maintains the second rank, it loses a significant portion of its advantage. A comparison of Clean sub-fields to their corresponding benchmark categories in Figure 7b reveals that Artificial Intelligence innovation now takes the lead while Building Fabric and, notably, Smart Systems, lose ground. Collectively, these observations suggest robust incentives for national governments to subsidize Clean, despite the advantage of Clean being more pronounced when taking a more global perspective of value creation.

Figure 7: Local returns – weighted average across countries



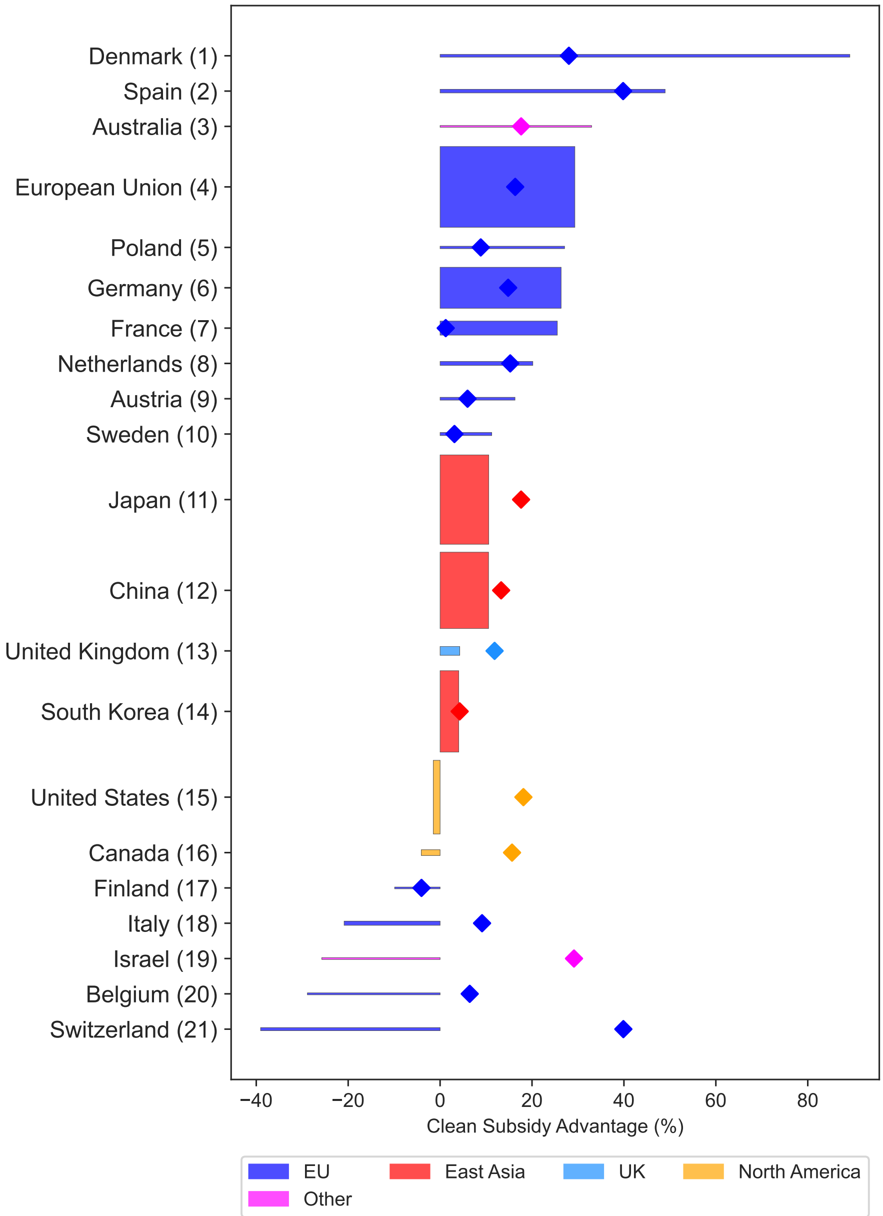
Notes: Expected local return rates to R&D subsidies by technology field (y-axis) along with 95% confidence bands. The (vertical) width of a bar indicates the field size, measured by its number of innovations. The x-axis displays the return rate (in %) to an additional $1 of R&D subsidy in the field, with returns based on the spillover value that subsidy-induced innovation creates within the country of origin between 2009 and 2018 (i.e., $ReturnRate_a$ in equation 1 where SV_i is the local spillover value from Figure 10b). The left-hand figure includes the entire sample of innovations, divided into Clean and 5 other broad sectors. The right-hand figure compares sub-fields within Clean (see Appendix B for a detailed description) to several trending technology fields. The dotted line represents the weighted average across technology fields for the sample under consideration. For comparison, the light-shaded bars and dotted lines repeat the results for global returns of Figure 4.

Figure 8 probes further into the cross-country variability of the Clean Subsidy Advantage (CSA) indicator from the vantage point of local returns. The horizontal dimension of the bars shows the local returns of Clean for each country, divided by the weighted average returns. The width represents the number of clean innovations for a given country. The diamonds represent the CSA from a global spillover perspective (thus corresponding to the height of the bars in Figure 5). Interesting patterns emerge when considering the major innovation blocs. Compared to the global return rates analysis, the CSA premised on local returns diminishes notably for China (from 13.3% to 10.5%) and Japan (from 17.6% to 10.6%) and entirely dissipates for the US (from 18.1% to -1.5%). The CSA for Korea remains virtually unaltered. In contrast, the EU's CSA almost doubles (from 16.3% to 29.3%). This pattern suggests that the benefits accruing from clean innovations in the EU are relatively more likely to be retained within EU borders, compared to those in other fields. Given that innovation policy is implemented both at the

EU and national levels, it is compelling to look at local return rates at the level of individual countries. This reveals a mixed picture, with major innovators such as Germany and France demonstrating substantial incentives to invest in Clean subsidies based on national (growth) interests. Conversely, Italy and Switzerland exhibit a pronounced Clean subsidy *disadvantage*.

The two following sections flesh out these patterns in greater detail, contributing to current policy debates. Section IV aims to contribute to the discourse about the advisability of a supranational strategy toward clean innovation policy. Section V offers a fresh perspective on the ongoing discussion surrounding the US government's Inflation Reduction Act (IRA), which has triggered worries in the EU regarding possible adverse impacts on its competitiveness.

Figure 8: Clean Subsidy Advantage by country – Local returns



Notes: Clean Subsidy Advantage by country (y-axis). The (vertical) width of a bar scales with the number of clean innovations in the country. All countries in our sample with at least 2000 clean innovations are included. The Clean Subsidy Advantage for a country (on the x-axis) is calculated by dividing the local return rate from an extra subsidy in Clean by the weighted average local return rate across all country innovations. We then subtract one and multiply by 100% (it corresponds, for each country, to the height of the green bar, divided by the dotted line in Figure 7). For comparison, each country's Clean Subsidy Advantage based on *global* returns from Figure 5 is also displayed (diamonds).

IV. Supranational clean innovation policy design

A. *Motivation*

In the majority of countries examined, the clean subsidy would yield spillover returns that surpass those in the majority of other technology sectors. However, it's important to remember that Clean covers a wide range of technologies spread across different areas of knowledge. For instance, wind energy production mainly relies on the arrangement and combination of mechanical parts, biomass depends on concepts in agriculture and chemistry, and smart systems need expertise in electronics and data science. As shown in Figures 4b and 7b, the returns across these Clean technology areas vary considerably. Additionally, the returns for each of these areas could differ by country. In this section, we apply our method to help shape clean policy with this more detailed perspective.

Our focus here is on the potential advantages that could arise from a coordinated, supranational approach to clean innovation policy. The value of such coordination is fundamentally tied to the variance in the prioritization of fields across different countries. Imagine a simplified scenario with only two regions, Country 1 and Country 2, and three distinct Clean subfields: A, B, and C. Assuming that these fields are ranked A-B-C based on local returns from a subsidy, both countries could improve upon an undifferentiated clean subsidy strategy by implementing a targeted policy, allocating more resources to Field A over B, and B over C. Now, suppose that for Country 1, the ranking based on *global* returns is also A-B-C, while for Country 2, it is C-B-A. The two regions would jointly benefit by coordinating a policy where Country 1 focuses its subsidies on Field A, and Country 2 on Field C. Alternatively, the best course of action could involve directing all subsidies to Country 1 if even its lowest-ranked field generates greater collective returns than the top-ranked field in Country 2. This is the primary mechanism we explore in this section.

B. *Policy design simulation set-up*

We create a straightforward policy design simulation to gauge the extent of potential benefits that might be obtained from supranational coordination. Within this exercise, we assume that countries know the ranking of clean subfields, both in terms of local and supranational returns. These supranational returns refer to returns at the aggregate level of a group of countries under consideration (for instance, the EU). The simulation investigates the impact of a policy that increases the total quantity of Clean innovation by 1%. To estimate the advantages of supranational coordination, we compare the weighted average supranational return rate under two distinct scenarios: (1) Subsidies are assigned according to the ranking of return rates realized within individual country borders. (2) Subsidies are allocated following the ranking of return rates accrued at the supranational level. In the second scenario, the existence of country borders is disregarded when evaluating returns, which are maximized as if the collection of countries formed a unified innovation policy consortium. We additionally impose the restriction that the innovation output in any particular subfield can increase by no more than 10%. This is done with the understanding that return rates are computed using the marginal subsidy, without factoring in the diminishing marginal returns of a subsidy as the subsidy amount grows larger.[11]

It is important to highlight that the supranational returns in the nationally optimal must be lower than those in the supranationally optimal one. The focus of our question is not on whether there is a difference, but rather on the size of the difference. This is largely contingent on the degree to which local return rate rankings diverge from global return rates, and whether there are subfields within individual countries that generate particularly strong spillovers benefiting the broader supranational grouping of countries.

C. Results

Figure 9 summarizes the findings of our policy simulation. The white and black diamonds, aligned with the upper x-axis, denote the weighted average return rate for the two distinct policy scenarios. The orange bars, in correspondence with the lower x-axis, represent the relative increase in return rates, obtained by dividing the return rate represented by the black diamond by that of the white diamond.

Firstly, let us analyze the absolute return rates, denoted by the black and white diamonds. The country groups are arranged in order of their size, measured in terms of the number of innovations. Notably, both under the optimal national and supranational targeted policies, return rates rise with the size (in terms of innovation) of the country group. This is to be expected, as the larger the country group, the larger the pool of R&D benefiting from the spillovers induced by a subsidy. Focusing on the global returns from a nationally optimal targeted policy, we observe an overall return rate of 161%. Comparing this to the return rate of 135% for an untargeted subsidy scheme in Clean technology (as shown in Figure 4a), we infer that the capability to target subfields, even when driven solely by national interests, enhances returns by 26 percentage points.

[11]A thorough analysis of this aspect requires assumptions on the abundance of ideas far below the marginal idea quality thresholds, as well as potential general equilibrium dynamics in the reallocation of capital and labor when subsidies in a field become substantial. While this topic is undeniably important and interesting, it falls outside the remit of the current study.

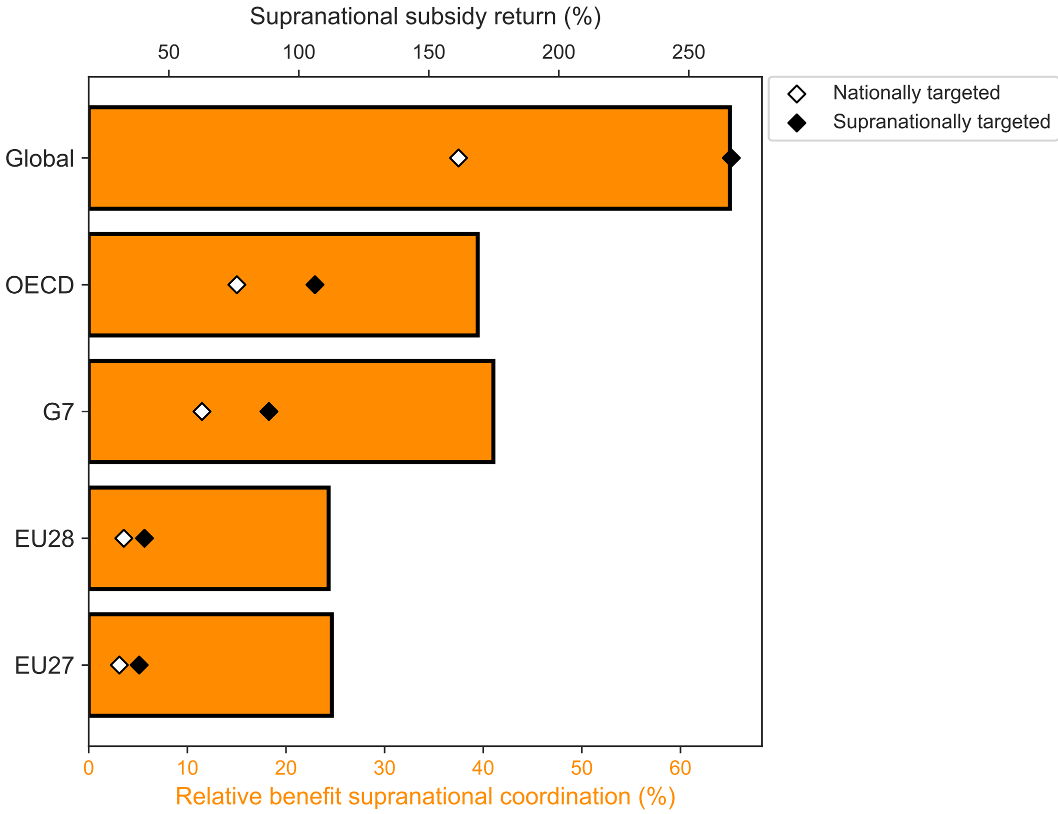
The benefits from this targeted approach, as shown by the orange bars, are substantial and generally rise with the size of the innovation base. For both the EU27 and the EU28 (including the UK), return rates experience an increase of approximately a quarter when innovation policy is coordinated. The advantage for the G7 and the OECD is around 40%. This implies that a combined innovation policy, which incorporates the major European economies along with the US and Japan, exhibits considerable potential benefits. The highest rate of return is delivered by a globally coordinated policy, yielding 2.6 dollars for each dollar invested, and the coordination effort produces the largest relative benefit, at 65%.

Upon scrutinizing these supranationally optimized policies more closely, it is clear that a select few countries tend to absorb the bulk of the allocated Clean subsidy. For instance, under an OECD-wide policy, US Clean innovation sectors receive 92.6% of the subsidized innovations, followed by Canada at 3.6% and Israel at 2.3%, with merely eight countries obtaining subsidies at all. The significantly larger benefits yielded by global coordination as opposed to mere OECD coordination stem from the inclusion of China in the policy. In fact, the optimal policy allocates 83.9% of its subsidies to China and a mere 12.7% to the US, with Switzerland ranking third at 1.3%. At the EU28 level, Germany receives the majority of the allocation (54.0%), followed by Denmark (15.4%) and the UK (10.8%). At the EU27 level, Austria overtakes the UK to secure third place, receiving 11.8% (in this case, Germany and Denmark receive a share of 62.6% and 17.0%, respectively).

Collectively, these results underscore the considerable potential to enhance the creation of (social) value by coordinating clean innovation policy at broader geographic scales. However, it must be acknowledged that the optimal policies may prove politically challenging, as they may necessitate the exclusion of numerous countries from the stimulus program.[12]

[12] Subsequent research could employ our methodological framework to construct an optimal policy imposing constraints informed by political considerations.

Figure 9: Benefits of supranational coordination



Notes: Results of policy simulation to determine benefits of supranational coordination. The y-axis denotes supranational country groups. White diamonds (upper x-axis) depict weighted average returns per dollar in a scenario where each country prioritizes clean tech subfields according to local returns. Black diamonds (upper x-axis) show returns when a supranational government allocates subsidies based on a ranking of country-fields by supranational returns. The orange bars (lower x-axis) represent the increase in return rates due to supranational coordination, calculated by dividing the value of the black diamond by the white one.

V. Between-country flows of clean spillovers

A. Motivation

The analyses conducted thus far suggest that a global planner would have a significant preference for a targeted innovation policy towards Clean, compared to flat incentive schemes that distribute public resources evenly across the innovation landscape. Yet, only a relatively small fraction of productivity growth induced by knowledge spillovers is retained within jurisdictional borders. This implies that a substantial part of any subsidy spills over, benefiting other nations. Conversely, this indicates that any country *benefits* from ‘knowledge transfers’ even in the absence of national innovation policy. These observations raise an important question: who, on net balance, reaps the benefits and who provides the knowledge spillovers that their subsidies generate?

We believe that this question bears relevance in shaping policy responses to the US government's Inflation Reduction Act (IRA). The IRA has initiated an intense policy debate, particularly in Europe, driven by concerns regarding its impact on the competitiveness of firms outside the US. The IRA comprises a $400 billion climate-related stimulus package dispersed over a decade. While such a large-scale commitment, akin in magnitude to the EU's clean stimulus, is lauded in principle, the crux of the controversy resides in its protectionist elements. A substantial segment of the stimulus package includes clauses mandating sourcing and production within the US, thereby infringing World Trade Organization rules (Kleimann et al., 2023).[13] In response to these constraints and with the objective of restoring a level playing field, propositions have surfaced to replicate US policy by enhancing EU-centered support and relaxing state aid rules. These proposals have been championed by notable figures such as France's President Macron and President of the European Commission von der Leyen.[14]

The appropriateness of such assertive responses, which carry the risk of provoking further protectionist policies, straining scarce resources, diminishing productivity by disrupting global markets, and jeopardizing diplomatic relationships, depends on the overall negative consequences of the IRA. We assert that the value of knowledge spillovers is an overlooked factor in the discussion. The efforts of each of the major blocs to stimulate demand for clean products will spur innovation by rendering previously inframarginal innovation ideas viable. Consequently, the associated knowledge spillovers should be incorporated into the analysis.

B. Measuring between-country spillovers

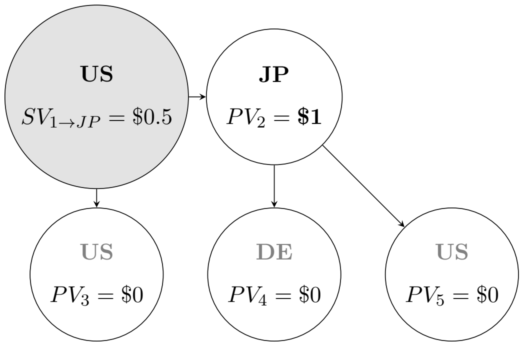
P-rank, as outlined in expression 2, enables partitioning spillover value by country of origin and destination. We have already leveraged this capability to compute the retention of knowledge spillovers within a country's boundaries (refer to Section III B). Building on the same principle, we can compute the flow of knowledge spillovers between pairs of countries. Figure 10 demonstrates how we compute the SV_1 – that is, the spillovers generated by a US invention – that stream to Japan (as depicted in Figure 10a) and to Germany (as shown in Figure 10b). As before, we run the algorithm after zeroing out all destination countries not pertinent to our analysis. This process yields a measure for SV_i for each i within the network.

[13] Kleimann et al. (2023) provides an insightful examination of the IRA's potential repercussions on international trade, EU competitiveness, and the global climate transition.

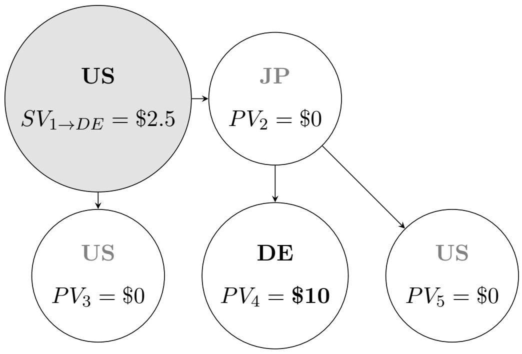
[14] Leigh Thomas,"Explainer: Why the U.S. Inflation Reduction Act has Europe up in arms", Reuters, https://www.reuters.com/markets/why-us-inflation-reduction-act-has-europe-up-arms-2022-12-05/ (accessed May 2023)

Figure 10: Calculating between-country spillovers

(a) SV to Japan



(b) SV to Germany



Notes: Illustration of the calculation of between-country knowledge spillovers. The spillover network is identical to the one in Figure 6. Circles represent patented innovations, with country codes indicating the patent's inventors. Lines represent citations between patent families. To calculate the spillover of innovation 1 to Japan, we simply set all private values of innovations that are not from Japan to zero (upper panel), and repeat our spillover value calculation. We see that $SV_{1\to JP} = \sigma(PV_3 + PV_2) + \sigma^2(PV_4 + PV_5) = 0.5(\$0 + \$1) + 0.5^2(\$0 + \$0) = \$0.5$. Similarly, to calculate the spillover of innovation 1 to Germany, we set all private values of non-German innovations to zero, and adapt our calculation accordingly: $SV_{1\to DE} = \sigma(PV_3 + PV_2) + \sigma^2(PV_4 + PV_5) = 0.5(\$0 + \$0) + 0.5^2(\$10 + \$0) = \$2.5$. Once we have calculated the spillover flows to a given country for all innovations in the sample, we can sum up over the relevant innovations to calculate total spillover value flows between the countries of interest.

By leveraging this approach, we can rework the return rate from equation 1, incorporating only spillovers realized within the geographic context pertaining to our analysis. For example, we may aim to discern the spillover value generated within Japan from subsidizing US innovations. Let $SV_{i\to JP}$ represent the spillover value instigated by any innovation i towards Japan. The return rate to Japan of subsidizing US innovation in field a can then be formulated as:

$$ReturnRate_a^{US\to JP} = \frac{1}{c_a}\frac{1}{\#A^{US}}\sum_{i\in A^{US}} SV_{i\to JP} \times (\alpha_a - \alpha_a \times \mathbb{I}\{PV_i > 2c_a\} + \mathbb{I}\{PV_i < 2c_a\}) \quad (3)$$

Here, A^{US} denotes the set of innovations stemming from the US. This equation enables us to replicate our analysis of return rates, with the sole difference that the recipient of the spillovers is not necessarily the creator. The return rates reported show the benefit to country A (here, Japan) to subsidize innovation in country B (here, the US), taking into account the spillover value created by country B innovations to country A innovations. To obtain the absolute benefit to country A when country B pays for the subsidy, we add one to the return rate obtained in equation 3.

C. Results

Figure 11 visualizes the subsidy return flows between the five regions that are leading in terms of innovation. The top figure represents the weighted average across all innovations for each given country pair, while the bottom figure specifically focuses on Clean technology. The arrows pointing to the right (left) display the returns harvested in the country on the right (left) from a subsidy in the country on the left (right). The bar represents the net result by subtracting one from the other.

When considering innovation as a whole in figure 11a, it is evident that the most substantial interaction occurs between the US and Europe. Should Europe invest one dollar to support US innovation, it would reap benefits amounting to 18 cents. On the flip side, the US receives roughly 15 cents for each euro invested in Europe. Overall, the US exports spillover value to China, while it receives from Japan 2.8 percentage points more than it contributes. The balance with Korea is approximately zero. Japan emerges as the most significant benefactor, serving as a net exporter of knowledge flows to all regions considered, most notably to Korea.

In the context of *clean* innovation subsidy return rates, the imbalances are considerably more pronounced, particularly where the US and Japan are concerned. Japan stands as a net exporter of clean returns to Korea (10.5 percentage points), Europe (6.8 percentage points), China (3.1 percentage points), and the US (2.5 percentage points). European nations are significant beneficiaries of the US and Japan, maintaining a near balance with China and Korea. China primarily receives from the US (although to a much lesser degree than Europe, with -3.7 percentage points), Japan (-3.1), and Korea (-1.8), and provides minimally to Europe (0.9).

Turning to the discourse surrounding the IRA, our analysis indicates that historically, US subsidies have generated a considerably higher value in Europe compared to the reciprocal effect. Should the EU and the US have allocated one dollar each to subsidizing Clean R&D, Europe would have received an additional benefit of 12.3 cents. It should be noted, however, that both blocs significantly benefit from each other's knowledge production – to a much greater extent than any other pair – with subsidy return flows of 13.3 cents to the dollar (from EU to US) and 25.6 cents (from US to EU). From the perspective of Europe, the innovation incentives induced by the IRA can be compared to a subsidy it does not pay for. A clean subsidy of 1 dollar paid for by the US government would create 1.26 dollars of spillover value in Europe. An untargeted policy, instead, would create 1.18 dollars. In other words, compared to a scenario in which the US would not increase innovation support at all, the benefits – based on this historical analysis – to the EU are large, and the benefits from clean support exceed those from an untargeted policy.

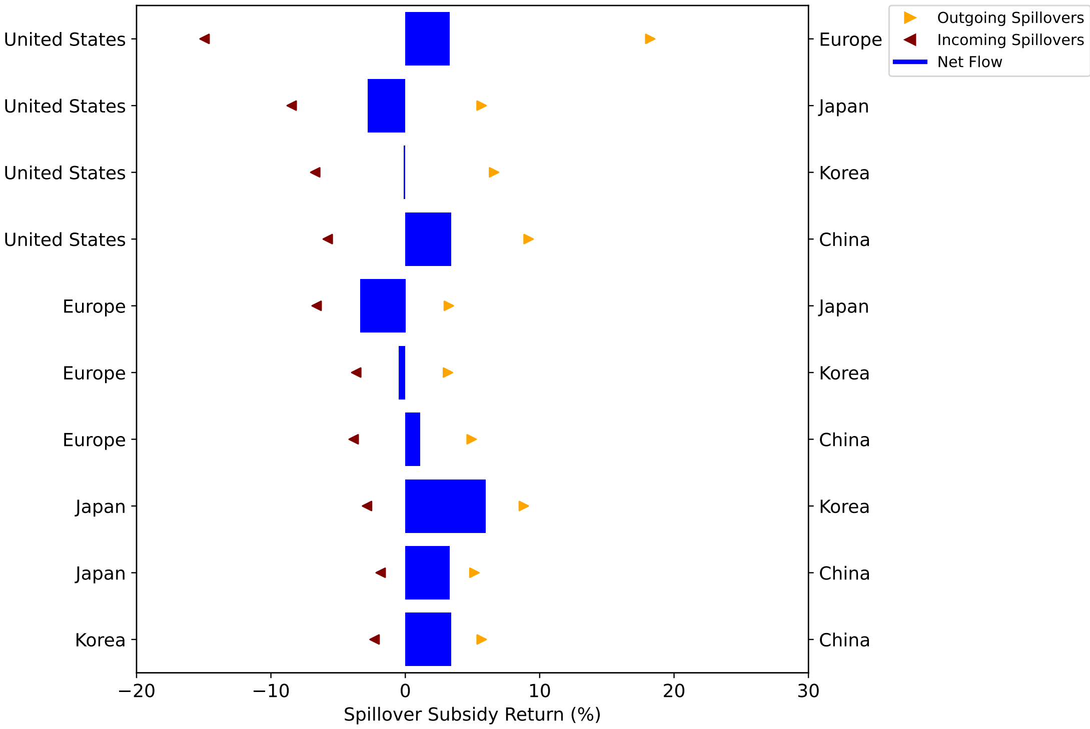
Our objective here does not extend to contrasting the magnitude of these spillover effects with the potential repercussions of protectionist measures or performing a comprehensive equilibrium analysis to propose optimal strategies. Nonetheless, it is essential to recognize that the figures suggested here bear significant economic relevance. Interpreting these results directly in the context of the IRA is not straightforward because not all IRA subsidies will necessarily foster an increase in R&D activities. However, two reference points might prove useful.

Consider a scenario where this clean initiative brings about the same change in R&D costs as a direct subsidy that is one-tenth of its size ($40 billion). Over the decade during which the program is executed, the knowledge spillover channel could yield benefits to the EU amounting to approximately $10 billion. As a secondary reference, we can examine the aggregate spillover quantities over our observation period. Figure 13 in Appendix A provides information about such Clean flows. Throughout the ten years considered, Clean innovations from the US have produced spillovers in the EU estimated at $150 billion. If the IRA boosts this by 10%, it could confer a $15 billion benefit to Europe.

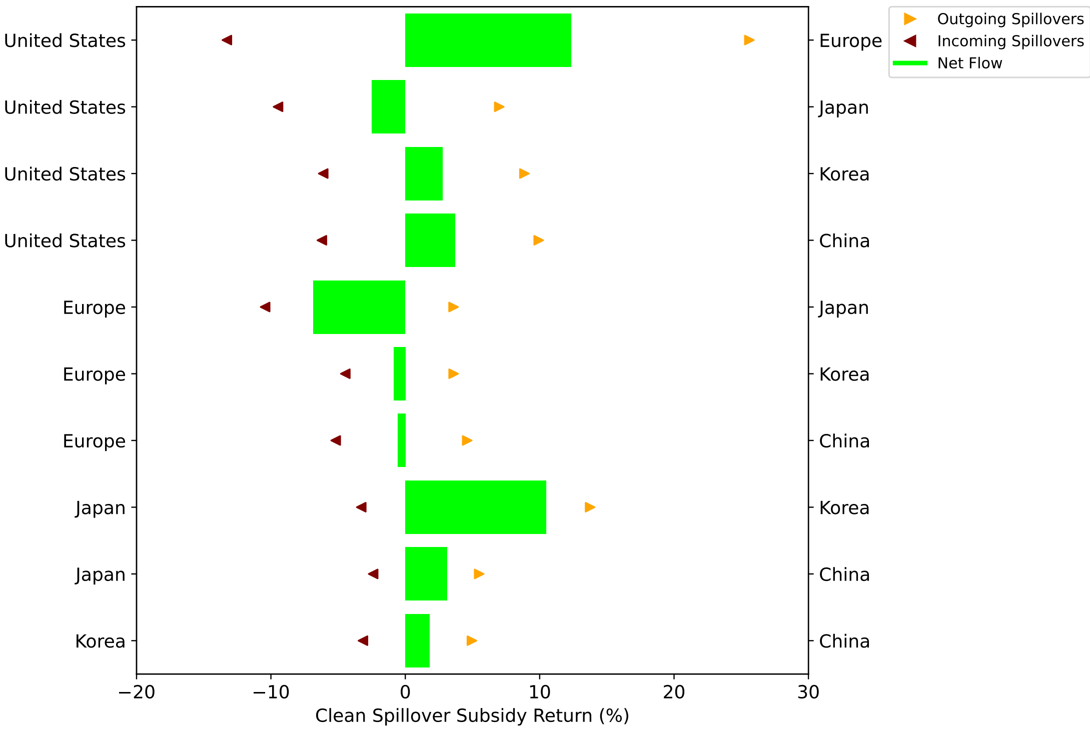
Rather than offering confident forecasts, these estimates establish an order of magnitude. A more exhaustive analysis is essential for guiding the significant policy decisions that all countries confronted with the IRA need to make. The principal takeaway is that the knowledge spillover channel merits serious consideration.

Figure 11: Subsidy return flows

(a) Overall



(b) Clean



Notes: Subsidy return flows between pairs of regions. Gold arrows pointing right represent the returns garnered by the region on the right from an additional subsidy in the region on the left (it shows $ReturnRate_a^{left \to right}$ from equation 3). Bordeaux arrows pointing left represent the returns gained by the region on the left from an extra subsidy in the region on the right. Bars denote the difference between the arrows: a net flow benefiting the region on the right (resp. left) results in a positive (resp. negative) number on the x-axis, which shows the return rates (arrows) in percentage terms and the differences (bars) in percentage point terms. Europe includes all EU27 countries and the UK. The upper figure perfoms the analysis for all technology sectors, the lower figure includes only return rates from clean subsidy.

VI. Conclusion

This paper provides a detailed examination of clean innovation policy and its implications at both the local and supranational levels. Our analysis brings several new insights to the innovation literature, beginning with the finding that the return rate on targeted clean subsidies exceeds that of most other fields, as well as that of untargeted, broad-based innovation policy. This highlights the economic value of purposeful, directed support for Clean innovation, and signals a potential direction for governments to enhance their innovation return rates. Taking this finding together with the fact that clean innovation produces an environmental externality – which is hard to estimate but likely large – suggests clean innovation support is a win-win strategy.

Second, we delve into the potential benefits of supranational coordination in Clean innovation policy. Our findings indicate that while such coordination could deliver significant value, the political implementation may prove complex due to the uneven distribution of support that would be entailed in an optimal policy. This presents a clear, albeit difficult, opportunity for international collaboration in the pursuit of cleaner, more sustainable technologies. Despite the challenges, the potential rewards underscore the importance of continued exploration of such coordinated efforts. Altogether, our results underscore the need for nuanced, geographically aware, and targeted policy approaches to support clean innovation and maximize its societal benefits effectively.

Last, our study examines the spatial distribution of innovation spillovers, revealing that a relatively small proportion is localized within the country of origin. When national interests are myopically followed, Clean loses some of its attractiveness (but remains ranked highly) in many countries (especially the US, but not the EU). We observe that spillover flows are uneven across countries, leading to certain nations 'giving away' more than they 'receive' from their clean innovation efforts. These insights provide valuable context for ongoing policy debates, such as those concerning the Inflation Reduction Act (IRA) in the US.

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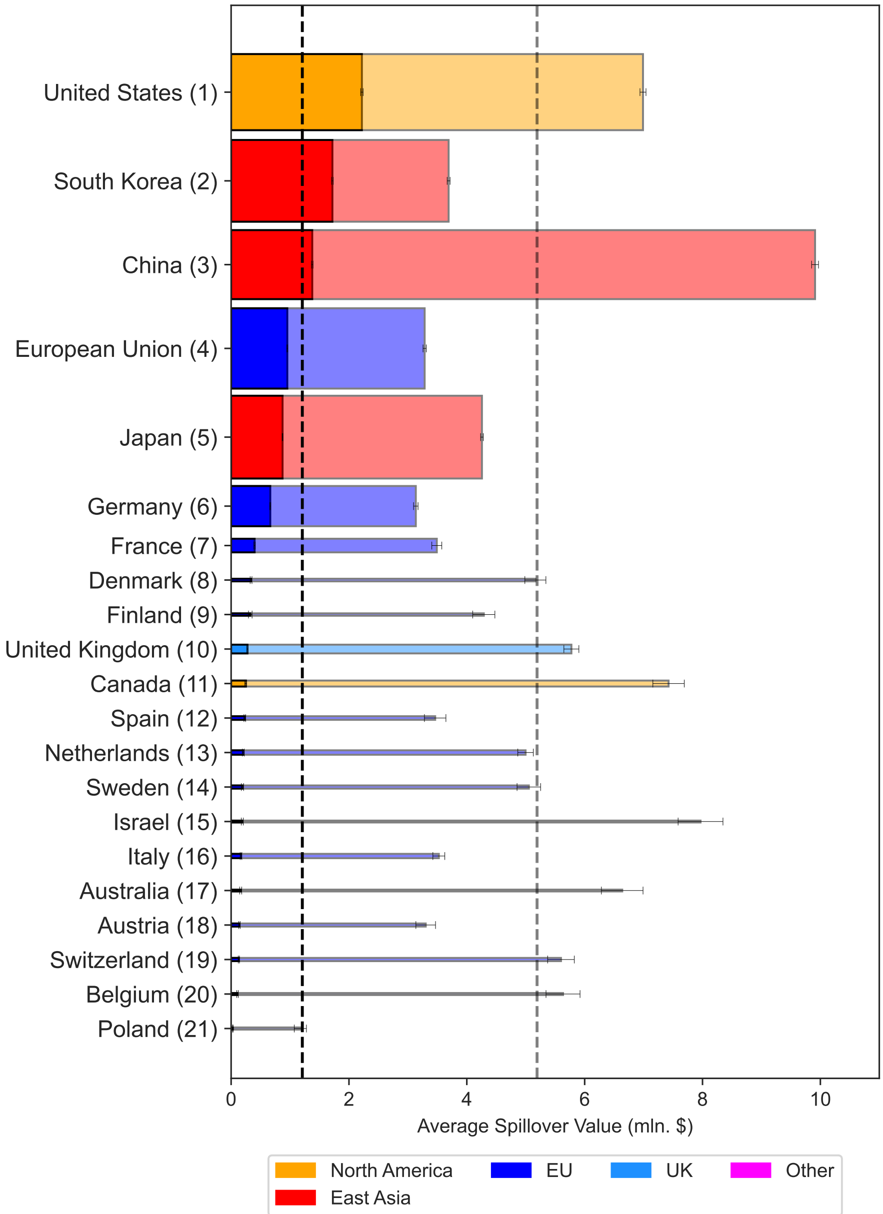
Appendix

A. Additional results

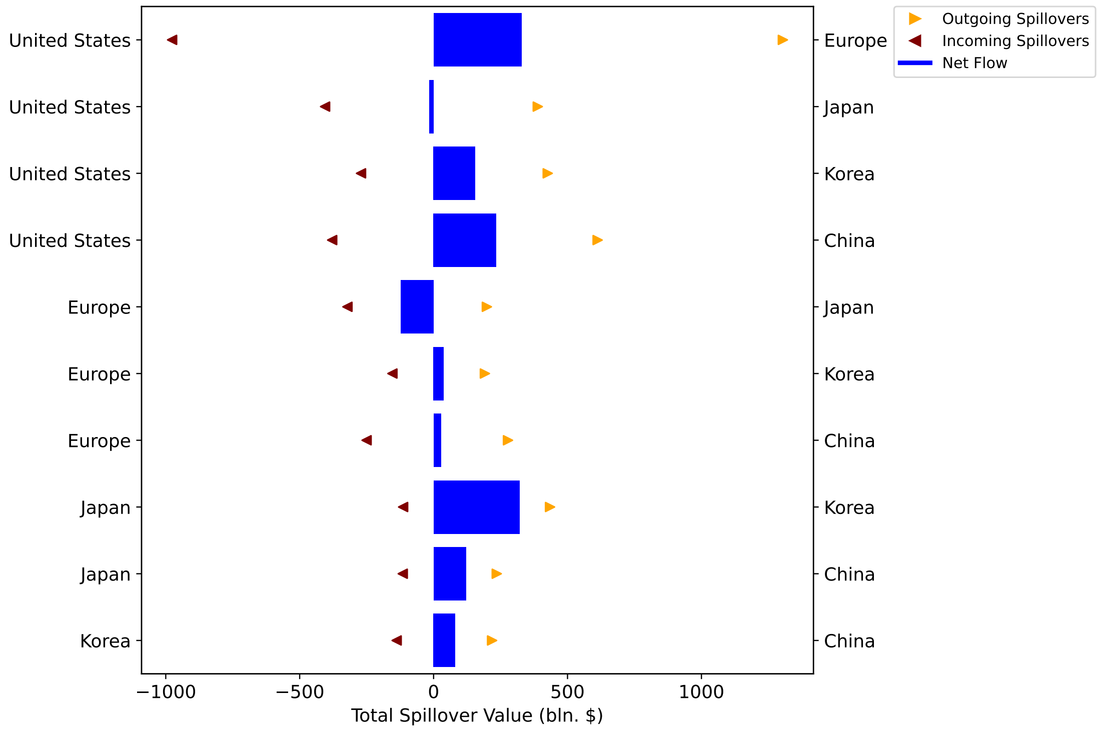
Figure 12: Localization of spillover value – clean innovations



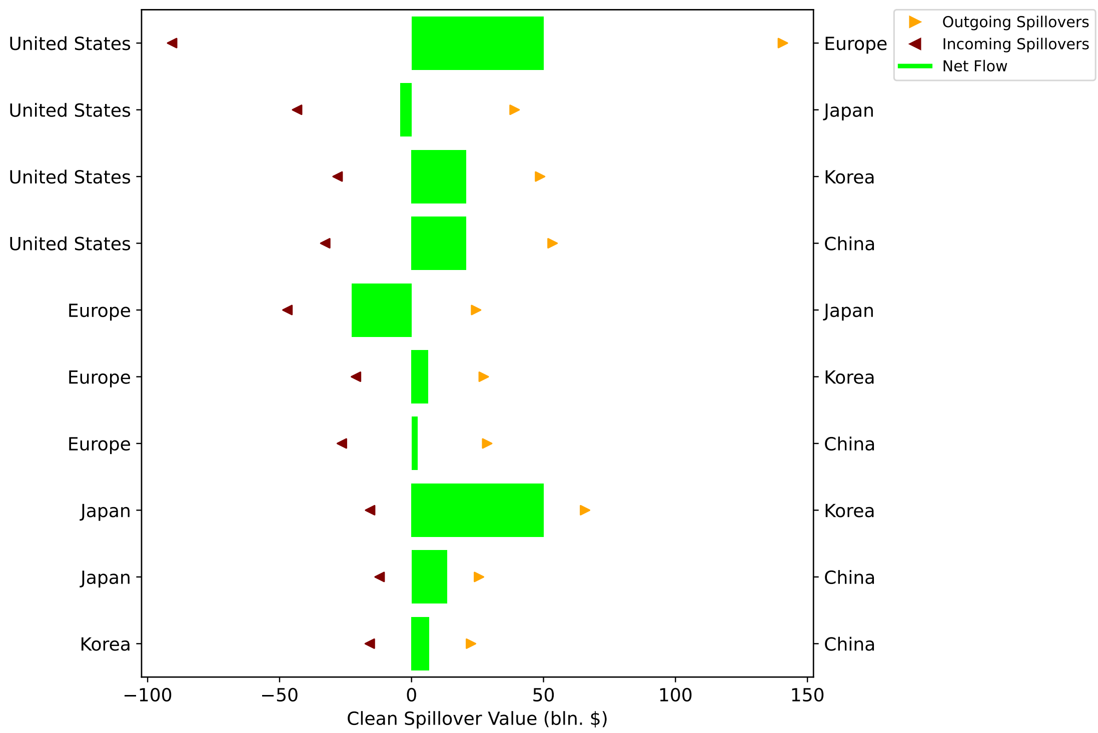
Notes: Average spillover value by country (y-axis) along with 95% confidence bands. The (vertical) width of a bar scales with the number of clean innovations in the country. The x-axis displays the average local (dark-shaded bars) and global (light-shaded bars) spillover value of clean innovations in the country. It is the average SV_i over all clean innovation in a country (expressed in millions of 2015 US dollars) as calculated in Figure 6b and Figure 6a respectively.

Figure 13: Spillover value flows

(a) Overall



(b) Clean



Notes: Spillover value flows between pairs of regions. Gold arrows pointing right represent the total spillover value garnered by the region on the right from innovations of the region on the left (it shows $\sum_{i \in A^{left}} SV_{i \to right}$ from equation 3). Bordeaux arrows pointing left represent the total spillover value gained by the region on the left from innovations originating in the region on the right. Bars denote the difference between the arrows: a net flow benefiting the region on the right (resp. left) results in a positive (resp. negative) number on the x-axis, which shows spillover values in billions of 2015 US dollars. Europe includes all EU27 countries and the UK. The upper figure performs the analysis for all technology sectors, the lower figure includes only spillover flows from clean innovations.

B. Clean sub-field definition

The study leverages a novel classification framework for clean technology sub-fields. This system, designed by the Department for Business, Energy and Industrial Strategy (BEIS), involves an expert-validated method to gather patent codes relevant to the clean sub-fields scrutinized in the main body of the paper. In this section, we offer a synopsis of the methodology and provide the patent codes for each sub-fields, displayed in the tables below.

The extraction of codes followed a four-stage process. Initially, an innovation framework was established, capitalizing on the findings outlined in the Energy Innovation Needs Assessment (EINA) by Vivid Economics (2019). This scheme facilitated the development of a custom assortment of search terms extracted from innovation prospects in the UK. The search terms secured a comprehensive yet precise scope of patents that coincide with BEIS' innovation initiatives.

In the second stage, the search terms from the 'sub-technology' breakdown were used to collect candidate classes via the CPC Espacenet Classification search tool. For each Clean sub-field in the tables below, we report the sub-technology and its components where relevant, along with the CPC codes identified. These codes were used to extract a sample of patents that were used as the input for expert assessment.

In the third step, BEIS engineers thoroughly analyzed the retrieved patents. This evaluation aimed to gauge the level of relevance exhibited by each patent code in relation to the EINA framework. Based on the patent documents, engineers employed their expertise to provide an estimate of the extent to which each patent code aligned with the framework.

The fourth and final step of this process involved conducting a benchmarking exercise to validate the derived patent codes by comparing them with existing academic studies. Specifically, BEIS searched for published academic articles that presented a comprehensive list of patent codes for each sector. This benchmarking step ensured that no essential patent codes were overlooked.

The categorization of the Clean technology landscape, even when consulting engineering experts, involves a degree of personal judgment. As part of this process, experts indicated their confidence level – Low, Medium, or High – when classifying specific classes into corresponding sub-fields. We only retained the CPC codes classified with Medium or High confidence. The respective confidence levels are disclosed in the third column of the ensuing tables.

Table 2: Biomass & Bioenergy Patent Codes

Sub-technology	Patent Codes	Confidence
Component • Scale-up • Deployment • Link to CCUS • Renewable hydrogen	Y02E 50/00: Technologies for the production of fuel of non-fossil origin Biofuels, e.g. bio-diesel; Fuel from waste, e.g. synthetic alcohol or diesel	High
Gasifier • Feedstock • Gasifier • Syngas cleanup	C10J2300/0916: Details of gasification process, Biomass	High
BioH2 and Bio-SNG • Water-Gas Shift (WGS) Reaction	C12M21/04: Bioreactors or fermenters for producing gas, e.g. biogas.	Medium
Fischer-Tropsch Synthesis • FT Catalyst • FT reactor • Upgrading	C10G2300/1022: Aspects relating to hydrocarbon processing covered by groups: Feedstock Materials → Fischer-Tropsch products C01B2203/062: Integrated processes for the production of hydrogen or synthesis gas (Hydrocarbon production e.g. Fischer-Tropsch process)	High
Syngas to Methanol • Overall Process	C01B2203/061: Integrated processes for the production of hydrogen or synthesis gas (Methanol production)	High
Woody & Grassy Energy Crops -SRC & Miscanthus • Breeding & Crop R&D • Growing and harvesting, improving agronomics	A01C7/00: Sowing Seeds A01C 15/00: Fertiliser Distribution A01C 17/00: Fertisliser or seeders with centrifugal wheels A01C 19/00: Arrangements for driving working parts of fertilisers or seeders A01C 21/00: Methods of fertilising A01D45/30: Harvesting of standing crops (of grass-seeds or like seeds). A01H1/12: Processes for modifying genotypes → Processes for modifying agronomic input traits, (e.g. crop yield, drought, cold, pest resistence) Y02A 40/10	Medium
Novel Oil Crops • Breeding & Crop R&D • Growing and harvesting, improving agronomics	C11B1/00: Production of fats or fatty oils from raw materials (under head of vegitable oils).	High
Lignocellulosic feedstock pre-treatment & hydrolysis • Pre-treatment • Hydrolysis	C12P2201/00: Pretreatment of cellulosic or lignocellulosic material for subsequent enzymatic treatment or hydrolysis C08H8/00: Macromolecular compounds derived from lignocellulosic materials	High
Lignocellulosic ethanol • Overall process	C12P7/10: Preparation of Ethanol substrate containing cellulosic material	High
Syngas fermentation • Pre-treatment • Reactor • Bacteria	C12M21/04: Bioreactors or fermenters specially adapted or producing gas, e.g. biogas C10L3/08: Production of synthetic natural gas C10L3/10: Working-up natural gas or synthetic natural gas	High
Feedstock Pre-treatment • Pre-treatment	C10G2300/10: Feedstock materials (covers: waste, vegetal biomass, animal biomass, natural gas, gas hydrates, hydrocarbon fractions, Fischer-Tropsch etc) Y02P20/145: Feedstock of biological origin	Medium
Digestion	C12M21/04: Bioreactors or fermenters specially adapted or producing gas, e.g. biogas	Medium

Notes: Academic benchmark used for this sub-field: Johnstone et al. (2010)

Table 3: Building Fabric Patent Codes

Sub-technology	Patent Codes	Confidence
Pre-Construction and Design • New Build and Existing • New Build	Y02B10/00: Integration of renewable energy sources in buildings.	High
Materials and Components • New Build • (Some retrofits) • New Build and Existing	F24S: Solar Heat Collectors E06B3/24: Double Glazing E06B3/20: Vinyl wind frame E06B1/325: Thermal Break between Frames E04B1/74: Insulation materials E04B1/76: Heat insulation only E04F15/18: Floor Insulation E04D13/16: Roof Insulation F16L59/00: Thermal insulation of pipes F21Y2115/10: LEDs	High
Build Process • New Build and Existing	Y02B80/00: Architectural or constructional elements improving the thermal performance of buildings	High
Building Operation • New Build and Existing	Y02B90/00: Enabling technologies or technologies with a potential or indirect contribution to GHG emissions mitigation (Fuel cells in buildings & Smart Grids for buildings)	High
All • New Build and Existing	Y02B: climate change mitigation technologies related to buildings, e.g. housing, house appliances or related end-user applications	High

Notes: Academic benchmark used for this sub-field: Noailly (2012)

Table 4: Carbon Capture, Use & Storage Patent Codes

Sub-technology	Patent Codes	Confidence
Power • Gas post-combustion capture • Gas pre-combustion capture • Gas Oxy-combustion capture • Solid fuel Post- combustion capture • Solid fuel Pre-combustion capture • Solid fuel Oxy-combustion • CO2 Storage: Infrastructure & injection wells	Y02C20/00: Capture or disposal of greenhouse gases B01D53/00: Separation of gases or vapours; Recovering vapours of volatile solvents from gases; Chemical or biological purification of waste gases, e.g. engine exhaust gases, smoke, fumes, flue gases, aerosols Y02E20/18: Integrated gasification combined cycle [IGCC], e.g. combined with carbon capture and storage [CCS] Covered by Y02C20/00 Y02P90/70: Combining sequestration of CO2 and exploitation of hydrocarbons by injecting CO2 or carbonated water in oil wells	High
Industry • Cement • Chemicals • Iron & steel • Refining • Cross-cutting	Y02P40/18: Production of cement - Carbon capture and storage Y02P20/151: Technologies relating to chemical industry - Reduction of GHG emissions e.g. CO2 Y02P10/122: Technologies relating to metal processing - by capturing or storing CO2 B01D53/00: Separation of gases or vapours; Recovering vapours of volatile solvents from gases; Chemical or biological purification of waste gases, e.g. engine exhaust gases, smoke, fumes, flue gases, aerosols, Y02P70/10: Final consumer goods - Greenhouse gas capture.	High

Notes: Academic benchmark used for this sub-field: Sharifzadeh et al. (2019)

Table 5: Heating & Cooling Patent Codes

Sub-technology	Patent Codes	Confidence
Heat pumps • Heat source • System • Installation • Integration • O&M • Installation	F25B30/00: Heat Pumps	High
Heat networks • Design • Installation • Connection to heat user • Interface with heat user	Y02B30/00: Energy efficient heating, ventilation or air conditioning [HVAC] Y02A30/27: Relating to heating, ventilation or air conditioning [HVAC] technologies C09K5/00: Heat-transfer, heat-exchange or heat-storage materials, e.g. refrigerants; Materials for the production of heat or cold by chemical reactions other than by combustion	High
Heat storage • Heat source & sink • Heat store	F24S: Solar Heat Collectors Y02E60/14: Thermal energy storage F24H7/00: Storage heaters, i.e. heaters in which energy is stored as heat in masses for subsequent release	High
Cooling • Main Unit • System • Design • Control • O&M • Storage	F24F: air-conditioning; air-humidification; ventilation; use of air currents for screening F25B: refrigeration machines, plants or systems; combined heating and refrigeration systems; heat-pump systems	High

Notes: Academic benchmark used for this sub-field: Renaldi et al. (2021)

Table 6: Hydrogen Patent Codes

Sub-technology	Patent Codes	Confidence
Natural Gas Reforming • Integration with CCS • Reformer • Water-gas shift reactor • Reformer	Y02E60/30: Hydrogen Technology, Storage & Distribution C01B2203/02: Processes for making hydrogen or synthesis gas (reforming & partial oxidation) C01B3/00: Hydrogen; Gaseous mixtures containing hydrogen; Separation of hydrogen from mixtures containing it	High
Coal Gasification • Integration with CCS • Gasifier + Gas Purification Unit • Gasifier • Air Separation Unit (ASU)	C10J3/00: Production of combustible gases containing carbon monoxide from solid carbonaceous fuels	High
Electrolysis • Manufacturing • Cell • Cell • Purification Equipment • Purification Equipment • System Integration • Other Routes • Other Applications • Modelling	C25B1/02: Electrolytic production of inorganic compounds or non-metals > Hydrogen or oxygen > by electrolysis of water Y02E60/36 (Covered by Y02E60/30): Hydrogen production from non-carbon containing sources, e.g. by water electrolysis C25B11/00: Electrodes; Manufacture thereof not otherwise provided for	High
Delivery • Pressure Levels • Safety • Pipelines • Tube Trailers • Compression • Liquefaction Process • Alternative Carriers • Odorants • Sensors	F25J1/00: Processes or apparatus for liquefying or solidifying gases or gaseous mixtures Y02E60/34 (covered by Y02E60/30): Hydrogen Distribution F17C5/02: Methods or apparatus for filling containers with liquefied, solidified, or compressed gases under pressures > for filling with liquefied gases e.g. helium or hydrogen	High
Storage • Alternative Hydrogen Storage • Alternative Hydrogen Storage • Cavern Topside Facility • Underground Storage	Y02E60/32 (Covered by Y02E60/30): Hydrogen Storage	High
Refuelling Stations • Purification • Unloading Equipment • Verification • Design • Standardisation	C01B3/50: Separation of hydrogen or hydrogen containing gases from gaseous mixtures, e.g. purification	High
Fuel cells • Manufacturing • Manufacturing • SOFC • SOFC • PEMFC • PEMFC • Design • Grid Services	H01M8/00: Fuel cells; Manufacture thereof Y02E60/50 (Covered by Y02E60/30): Fuel cells	High

Notes: Academic benchmark used for this sub-field: Baumann et al. (2021)

Table 7: Industrial Clean Innovation Patent Codes

Sub-technology	Patent Codes	Confidence
Chemicals • Efficiency improvements • Low-carbon substitutes • Heat recovery and reuse • Recovery and recycling • Energy systems • Alternative process technologies • Clustering	Y02P20/00: Chemical Industry, includes: Process Efficiency, Feedstocks, Reduction of GHG emissions, Energy Recovery, Recycling catalysts/materials	High
Food & drink • Efficiency improvements • Low-carbon substitutes • Heat recovery and reuse • Recovery and recycling • Energy systems • Alternative process technologies • Clustering	Y02P80/00: Climate change mitigation technologies for sector-wide applications (note: not specific to food & Drink, but relevant for all sectors hence included)	High
Iron & steel • Efficiency improvements • Low-carbon substitutes • Heat recovery and reuse • Recovery and recycling • Energy systems • Alternative process technologies • Clustering	Y02P10/00: Technologies related to metal processing: Reduction in GHGs, using alternative fuels, using renewables, recycling, process efficiency	High
Cement • Efficiency improvements • Low-carbon substitutes • Heat recovery and reuse • Recovery and recycling • Energy systems • Alternative process technologies • Clustering	Y02P40/10: Production of Cement: energy efficiency, Fuels from renewables, CCS, Optimizing production methods	High
Pulp & paper • Efficiency improvements • Low-carbon substitutes • Heat recovery and reuse • Recovery and recycling • Energy systems • Alternative process technologies • Clustering	D21: paper-making; production of cellulose	Medium
Glass • Efficiency improvements • Low-carbon substitutes • Heat recovery and reuse • Recovery and recycling • Energy systems • Alternative process technologies • Clustering	Y02P40/50: Glass production, e.g. reusing waste heat during processing or shaping; improving yield and rejection rates	High
Ceramics • Efficiency improvements • Low-carbon substitutes • Heat recovery and reuse • Recovery and recycling • Energy systems • Alternative process technologies • Clustering	Y02P40/60: Production of ceramic materials or ceramic elements, e.g. substitution of clay or shale by alternative raw materials, e.g. ashes	High

Notes: No academic benchmark was found for this sub-field.

Table 8: Nuclear Fission Patent Codes

Sub-technology	Patent Codes	Confidence
Mining, Processing, Enriching, Fabricating	Y02E30/00: Energy Generation of Nuclear Origin, G21: NUCLEAR PHYSICS; NUCLEAR ENGINEERING	High
CAPEX – Components and systems	Covered by G21: Additive manufacturing technology, B33Y	High
CAPEX – Construction and materials	Covered by G21	High
CAPEX – Construction installation and commissioning	Covered by G21	Medium
Operations and Maintenance	Covered by G21	Medium
Decommissioning	Covered by G21	Medium
Waste Management	Covered by G21	High
Regulatory	Covered by G21	Medium

Notes: No academic benchmark was found for this sub-field.

Table 9: Offshore Wind Patent Codes

Sub-technology	Patent Codes	Confidence
Floating wind • Moorings • Floating Foundations • Dynamic Cables	B63B 21/00: Tying-up; Shifting, towing, or pushing equipment; Anchoring B63B 2035/446: Floating structures carrying electric power plants for converting wind energy into electric energy H01B7/12: Floating cables H01B7/045: Flexible cables, conductors, or cords, e.g. trailing cables attached to marine objects e.g. buoys, diving equipment, aquatic probes, marine towline	High
Turbines	Y02E10/70: Energy generation through renewable Energy sources (wind) F03D: Wind motors, control and rotation axis. . . etc F05B 2240/21: Components for wind turbines	High
Foundations • Foundation Optimisation • New Foundation Design	E02D27/00: Foundations as substructures E02D27/425	High
Advanced Wind Modelling	G06F 30/00: Computer Aided Design	Medium
Balance of Plant (Transmission) • Longer Distance Transmission • Grid Integration • Grid Layout • Array Cables • HVDC Substations • Substation Co-location	Y04S10/00: System supporting electrical power generation, transmission or distribution Y02E60/60: Arrangements for transfer of electric power between AC networks or generators via a high voltage DC link (HVDC) H02J 3/36: Arrangements for transfer of electric power between ac networks via a high-tension dc link H02J 2003/365: Equipment being or involving an electric power substation H02J 13/00034	Medium
Operations & Maintenance • Remote Access • Remote O&M • O&M Optimisation	F03D 17: Monitoring or testing of wind motors, e.g. diagnostics Y02P 80/00: Climate change mitigation technologies for sector-wide applications H02J 13/365: Adaptive control systems, systems automatically adjusting themselves to have a performance which is optimum according to some preassigned criterion G05B 13/00	High
Installation (and logistics) • Advanced Lifting • Innovative Installation Techniques • Assembly	F03D 9/00: Vessels or similar floating structures specially adapted for specific purposes and not otherwise provided B63B 2035: Wind motors specially adapted for installation in particular locations E03D 27	High
Energy storage • Offshore Wind Energy Storage • Alternative Energy Storage	Y02E 70/30: Systems combining energy storage with energy generation of non-fossil origin F03D 9/10	Medium
Decommissioning & End of Life • Decommissioning • Repowering • Life Extension	F05B 2240: Component	Medium

Notes: Academic benchmark used for this sub-field: Johnstone et al. (2010)

Table 10: Smart Systems Patent Codes

Sub-technology	Patent Codes	Confidence
Smarter markets • Market platforms and aggregation	Y04S50/00: Market activities related to the operation of systems integrating technologies related to power network operation and communication or information technologies Y04S: systems integrating technologies related to power network operation, communication or information technologies for improving the electrical power generation, transmission, distribution, management or usage, i.e. smart grids	High
Demand side response • DSR – Homes/ buildings • DSR – EV integration	Covered by Y04S	High
Electricity storage • Bulk storage • Distributed storage • Distributed storage • Fast response storage	Y04S10/14: Energy Storage Units Y02E70/30: Systems combining energy storage with energy generation of non-fossil origin Y02E60/10: Energy Storage Using Batteries Y02E60/16: Mechanical energy storage, e.g. flywheels or pressurised fluids Y02E60/13: Energy storage using capacitors	High
Vector coupling • Power-to-gas	C25B1/02: Electrolytic production of inorganic compounds or non-metals > Hydrogen or oxygen > by electrolysis of water Y02E60/36: Hydrogen production from non-carbon containing sources, e.g. by water electrolysis C01C1/00: Ammonia; Compounds thereof	Medium
Networks • Networks	H02H9/00: Emergency protective circuit arrangements for limiting excess current or voltage without disconnection Y02E40/00: Technologies for an efficient electrical power generation, transmission or distribution	High
Applications of HPC, AI and ML in data-rich energy systems	G06F30/27: using machine learning, e.g. artificial intelligence, neural networks, support vector machines [SVM] or training a model G06F21/00: Security arrangements for protecting computers, components thereof, programs or data against unauthorised activity	Medium

Notes: No academic benchmark was found for this sub-field.

Table 11: Solar Patent Codes

Sub-technology	Patent Codes	Confidence
N/A	Y02E10/50: Photovoltaic [PV] energy H01L31/00: Semiconductor devices sensitive to infra-red radiation, light, electromagnetic radiation of shorter wavelength or corpuscular radiation and specially adapted either for the conversion of the energy of such radiation into electrical energy or for the control of electrical energy by such radiation; Processes or apparatus specially adapted for the manufacture or treatment thereof or of parts thereof H02S: Generation of electric power by conversion of infra-red radiation, visible light or ultraviolet light, e.g. using photovoltaic [pv] modules F24S: Solar Heat Collectors F03G6/00: Devices for producing mechanical power from solar energy	High

Notes: Academic benchmark used for this sub-field: Johnstone et al. (2010)

Table 12: Tidal Stream Patent Codes

Sub-technology	Patent Codes	Confidence
Structure & Prime Mover	Y02E10/20: Hydro energy Y02E10/30: Energy from the sea, e.g. using wave energy or salinity gradient F03B3/00: machines or engines for liquids	High
Power Take Off & Control	F03B15/00: Controlling Machines or Engines for Liquids E02B9/08: Tide or wave power plants	High
Foundations & Moorings	B63B2035/4466: Floating Structures carrying electric power plants (for converting water energy into electrical energy) E02D27/52: Submerged foundations B63B21/00: Tying-up; Shifting, towing, or pushing equipment; Anchoring	High
Connection	H01B7/12: Floating cables Flexible cables, conductors, or cords, e.g. trailing cables attached to marine objects e.g. buoys H01B7/045: diving equipment, aquatic probes, marine towline	Medium

Notes: Academic benchmark used for this sub-field: Johnstone et al. (2010)

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